Experiment 4

NAME	Shreya Shetty
UID	2019140059
CLASS	TE IT
BATCH	В
SUBJECT	NLP Lab

AIM: Classification using suitable classification model (NB)

THEORY:

What is Text Classification?

Text clarification is the process of categorizing the text into a group of words. By using NLP, text classification can automatically analyze text and then assign a set of predefined tags or categories based on its context. NLP is used for sentiment analysis, topic detection, and language detection. There is mainly three text classification approach

- 1. Rule-based System
- 2. Machine System
- 3. Hybrid System.

What is Naive Bayes?

Naive Bayes is a family of algorithms based on applying Bayes theorem with a strong(naive) assumption, that every feature is independent of the others, in order to predict the category of a given sample. They are probabilistic classifiers, therefore will calculate the probability of each category using Bayes theorem, and the category with the highest probability will be output.

Why Naive Bayes classifiers?

We do have other alternatives when coping with NLP problems, such as Support Vector Machine (SVM) and neural networks. However, the simple design of Naive Bayes classifiers make them very attractive for such classifiers. Moreover, they have been demonstrated to be fast, reliable and accurate in a number of applications of NLP.

Practical Example -

Let's say, we are given a sentence "A very close game", a training set of five sentences (as shown below), and their corresponding category (Sports or Not Sports). The goal is to build a Naive Bayes classifier that will tell us which category the sentence "A very close game" belongs to.

We could try applying a Naive Bayes classifier, thus the strategy would be calculating the probability of both "A very close game is Sports", as well as it's Not Sports. The one with the higher probability will be the result.

Expressed formally, this is what we would like to calculate P(Sports | A very close game), i.e. the probability that the category of the sentence is Sports given that the sentence is "A very close game".

Calculating P(Sports | A very close game).

Bayes' Theorem is useful for dealing with conditional probabilities, since it provides a way for us to reverse them.

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

In our case, the probability that we wish to calculate can be calculated as:

$$P(sports|a\ very\ close\ game) = \frac{P(a\ very\ close\ game|sports) \times P(sports)}{P(a\ very\ close\ game)}$$

IDE USED: Jupyter Notebook

DATASET USED: http://archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups

This data set is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups

LIBRARIES USED:

Nltk:

The Natural Language Toolkit (NLTK) is a Python package for natural language processing. NLTK requires Python 3.7, 3.8, 3.9 or 3.10. It can be installed as:

pip install nltk

scikit-learn:

Scikit-learn (formerly scikits.learn and also known as sklearn) is a free software machine learning library for the Python programming language. It features various classification,

regression and clustering algorithms including support-vector machines, Naïve Bayes etc. It can be installed as:

pip install scikit-learn

numpy:

NumPy is a library for the Python programming language, adding support for large, multidimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate. It can be installed as:

pip install numpy

matplotlib:

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It can be installed as:

pip install matplotlib

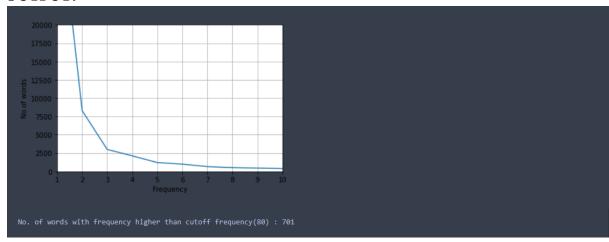
CODE:

```
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
stopwords = set (stopwords.words('english'))
print("Stop Words List :\n",stopwords)
for i in range(len(X_train)):
   word_list = []
   for word in X_train[i][1].split():
       word_new = word.strip(string.punctuation).lower()
       if (len(word_new)>2) and (word_new not in stopwords):
           if word_new in vocab:
               vocab[word_new]+=1
               vocab[word_new]=1
num_words = [0 for i in range(max(vocab.values())+1)]
freq = [i for i in range(max(vocab.values())+1)]
for key in vocab:
    num_words[vocab[key]]+=1
plt.plot(freq,num_words)
plt.axis([1, 10, 0, 20000])
plt.ylabel("No of words")
plt.grid()
num_words_above_cutoff = len(vocab)-sum(num_words[0:cutoff_freq])
print("No. of words with frequency higher than cutoff frequency({}):".format(cutoff_freq),num_words_above_
   if vocab[key] >=cutoff_freq:
       features.append(key)
X_train_dataset = np.zeros((len(X_train),len(features)))
for i in range(len(X_train)):
    word_list = [ word.strip(string.punctuation).lower() for word in X_train[i][1].split()]
    for word in word list:
            X_train_dataset[i][features.index(word)] += 1
print("X_TRAIN :\n",X_train_dataset)
```

```
X_test_dataset = np.zeros((len(X_test),len(features)))
for i in range(len(X_test)):
    word_list = [ word.strip(string.punctuation).lower() for word in X_test[i][1].split()]
    for word in word_list:
print("X_TEST :\n",X_test_dataset)
  def fit(self,X_train,Y_train):
              self.count[class_][i] = 0
           self.count[class_]['total'] = 0
           self.count[class_]['total_points'] = 0
       for i in range(len(X_train)):
           for j in range(len(X_train[0])):
  def __probability(self,test_point,class_):
      log_prob = np.log(self.count[class_]['total_points']) - np.log(self.count['total_points'])
      total_words = len(test_point)
          log_prob += current_word_prob
      return log_prob
  def __predictSinglePoint(self,test_point):
      best_prob = None
          log_probability_current_class = self.__probability(test_point,class_)
          if (first_run) or (log_probability_current_class > best_prob) :
              best_prob = log_probability_current_class
```

```
def predict(self,X_test):
         Y_pred = []
         for i in range(len(X_test)):
             Y_pred.append( self.__predictSinglePoint(X_test[i]) )
         return Y_pred
     def score(self,Y_pred,Y_true):
         for i in range(len(Y_pred)):
             if Y_pred[i] == Y_true[i]:
         return count/len(Y_pred)
nbModel = MultinomialNaiveBayes()
nbModel.fit(X_train_dataset,Y_train)
Y_test_pred = nbModel.predict(X_test_dataset)
print("Accuracy obtained :",nbModel.score(Y_test_pred,Y_test) )
print(classification_report(Y_test, Y_test_pred))
print("Sample Text for prediction from Testing Set:\n",X_test[1])
print("Prediction : ",nbModel.predict([X_test_dataset[1]]))
print("\n\nSample Text 2 for prediction from Testing Set:\n",X_test[0])
print("Prediction : ",nbModel.predict([X_test_dataset[0]]))
```

OUTPUT:



Features ['xref', 'cantaloupe.srv.cs.cmu.edu', 'newsgroups', 'path', 'subject', 'jesus', 'message-id', 'sender', 'usenet', 'news', 'organi zation', 'university', 'engineering', 'computer', 'network', 'references', distribution', 'date', 'tue', 'app', '1993', gatt', 'lines', 'note', 'whatever', 'says', 'latest', 'thing', 'like', 'good', 'even', 'better', 'comp.graphics', 'tiff', 'anything', 'college', 'program s', 'ibm, 'works', 'view', 'read', 'basic', 'jegg', 'gif', 'bmp', 'etc', 'thanks', 'post', 'looks', 'know', 'nntp-posting-host', 'reply-to', 'school', 'wed', 'article', 'writes', 'according', 'version', 'number', 'bytes', 'last', 'actually', 'l'e", 'sure', 'every', 'time', part', anyway', 'think', 'find', 'choice', file', 'use', 'support', 'word', 'either', 'l'e', 'found', 'many', 'matter', 'problems', a lso', 'important', 'help', 'define', 'little', 'bit', 'image', 'format', 'chris', 'get', 'opinions', 'mean', 'anybody', 'else', 'frank@del 2868.uucp', 'frank', 'o'dwyer', 'alt.atheism', 'behavior', 'mike', 'making', 'wrong', 'basis', 'come', 'question', 'idea', 'heard', 'on 'e', 'morally', 'necessarilly', 'steff', 'deal', 'necessary', 'keep', 'society', 'going', 'ohasis', 'come', 'question', 'idea', 'heard', 'on 'le', 'morall', 'postion', 'put', 'sometimes', 'hard', 'would', 'right', 'ie,' 'various', 'sort', 'possible', 'take', 'awa 'ny', 'object', 'way', 'problem', 'much', 'seem', 'agree', 'level', 'need', 'guess', 'thus', 'law', 'allows', 'believe', 'understand', 'standa rd', 'angument', 'based', 'quite', 'work', 'reason', 'known', 'advance', 'say', 'something', 'defined', 'cannot', 'exist', 'really', 'exist 'enem', 'de', 'group', 'instance', 'neallity', 'unless', 'information', 'defined', 'cannot', 'exist', 'really', 'exist 'enem', 'group', 'instance', 'neallity', 'unless', 'information', 'defined', 'cannot', 'exist', 'really', 'exist', 'newes', 'ma', 'win', 'reference', 'tell', 'esall', 'simply', 'indeed', 'upinion', 'dave', 'neaws', 'naw', 'min', 'nee', 'naw', 'naw', 'min', 'naw', 'naw', 'min', 'naw',

Accuracy obtained : 0.9533333333333334

Classification report for given Test Dataset :

	precision	recall	f1-score	support
alt.atheism	0.00	4 00	0.00	200
alt.acheism	0.98	1.00	0.99	280
comp.graphics	0.96	0.89	0.93	237
comp.os.ms-windows.misc	0.91	0.97	0.94	233
accuracy			0.95	
macro avg	0.95	0.95	0.95	
weighted avg	0.95	0.95	0.95	750

Sample Text for prediction from Testing Set:

('37937', 'Path: cantaloupe.srv.cs.cmu.edu!crabapple.srv.cs.cmu.edu!fs7.ece.cmu.edu!europa.eng.gtefsd.com!howland.reston.ans.net!usclente rpoop.mit.edu!eru.mt.luth.se!lunic!sunic!news.chalmers.se!pc5_b109.et.hj.se!d01-fad\nFrom: d91-fad\nFrom: d91-fad\nErom: d9

----\n';

Prediction : ['comp.graphics']
Given prediction : comp.graphics

REFERENCES:

- 1. https://medium.com/syncedreview/applying-multinomial-naive-bayes-to-nlp-problems-a-practical-explanation-4f5271768ebf
- 2. https://www.analyticsvidhya.com/blog/2020/12/understanding-text-classification-in-nlp-with-movie-review-example-example/
- 3. https://www.youtube.com/watch?v=60pqgfT5tZM
- 4. https://www.youtube.com/watch?v=temQ8mHpe3