LAB 1

LAB 1

## Feature extraction from 20 newsgroups documents

```
from os import listdir
from os.path import isfile, join
import string
```

```
from google.colab import drive
drive.mount('/content/drive')

dataset_path = "/content/drive/My Drive/Colab Notebooks/lab1"
import os
print(os.listdir(dataset_path))  # Verify that the dataset is accessible
```

```
Mounted at /content/drive
['utils.py', '20_newsgroups', '__pycache__', 'Untitled0.ipynb', 'Multinomial Naive Bayes- BOW with TF.ipynb']
```

```
my_path = "/content/drive/My Drive/Colab Notebooks/lab1/20_newsgroups"
```

```
#creating a list of folder names to make valid pathnames later
folders = [f for f in listdir(my_path)]
```

```
folders
```

```
['sci.med',
 'sci.electronics',
 'soc.religion.christian',
 'alt.atheism',
 'talk.politics.mideast',
 'sci.space',
 'talk.politics.guns',
 'talk.politics.misc',
 'talk.religion.misc',
 'comp.graphics',
 'comp.sys.ibm.pc.hardware',
 'comp.os.ms-windows.misc',
 'comp.sys.mac.hardware',
 'comp.windows.x',
 'rec.autos',
 'sci.crypt',
 'rec.motorcycles',
 'rec.sport.baseball',
 'rec.sport.hockey',
 'misc.forsale']
```

```
#creating a 2D list to store list of all files in different folders

files = []
for folder_name in folders:
    folder_path = join(my_path, folder_name)
    files.append([f for f in listdir(folder_path)])
```

```
import os
print(os.getcwd())  # Check current working directory
print(os.listdir())  # List all files and folders
```

```
/content
['.config', 'drive', 'sample_data']
```

```
#checking total no. of files gathered

sum(len(files[i]) for i in range(20))
```

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```
#creating a list of pathnames of all the documents
#this would serve to split our dataset into train & test later without any bias

pathname_list = []
for fo in range(len(folders)):
    for fi in files[fo]:
        pathname_list.append(join(my_path, join(folders[fo], fi)))
```

```
len(pathname_list)
```

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```
#making an array containing the classes each of the documents belong to

Y = []
for folder_name in folders:
    folder_path = join(my_path, folder_name)
    num_of_files= len(listdir(folder_path))
    for i in range(num_of_files):
        Y.append(folder_name)
```

```
len(Y)
```

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splitting the data into train test

```
from sklearn.model_selection import train_test_split
```

```
doc_train, doc_test, Y_train, Y_test = train_test_split(pathname_list, Y, random_state=0, test_size=0.25)
```

## functions for word extraction from documents

```
stopwords = ['a', 'about', 'above', 'after', 'again', 'against', 'all', 'am', 'an', 'and', 'any', 'are', "aren't",
 'be', 'because', 'been', 'before', 'being', 'below', 'between', 'both', 'but', 'by',
 'can', "can't", 'cannot', 'could', "couldn't", 'did', "didn't", 'do', 'does', "doesn't", 'doing', "don't", 'down',
 'each', 'few', 'for', 'from', 'further',
 'had', "hadn't", 'has', "hasn't", 'have', "haven't", 'having', 'he', "he'd", "he'll", "he's", 'her', 'here', "here
 'hers', 'herself', 'him', 'himself', 'his', 'how', "how's",
 'i', "i'd", "i'll", "i'm", "i've", 'if', 'in', 'into', 'is', "isn't", 'it', "it's", 'its', 'itself',
 "let's", 'me', 'more', 'most', "mustn't", 'my', 'myself',
 'no', 'nor', 'not', 'of', 'off', 'on', 'once', 'only', 'or', 'other', 'ought', 'our', 'ours' 'ourselves', 'out', '
 'same', "shan't", 'she', "she'd", "she'll", "she's", 'should', "shouldn't", 'so', 'some', 'such',
 'than', 'that',"that's", 'the', 'their', 'theirs', 'them', 'themselves', 'then', 'there', "there's", 'these', 'the
 "they'll", "they're", "they've", 'this', 'those', 'through', 'to', 'too', 'under', 'until', 'up', 'very',
 'was', "wasn't", 'we', "we'd", "we'll", "we're", "we've", 'were', "weren't", 'what', "what's", 'when', "when's", '
 "where's", 'which', 'while', 'who', "who's", 'whom', 'why', "why's",'will', 'with', "won't", 'would', "wouldn't",
 'you', "you'd", "you'll", "you're", "you've", 'your', 'yours', 'yourself', 'yourselves',
 'one', 'two', 'three', 'four', 'five', 'six', 'seven', 'eight', 'nine', 'ten', 'hundred', 'thousand', '1st', '2nd'
 '4th', '5th', '6th', '7th', '8th', '9th', '10th']
```

```
#function to preprocess the words list to remove punctuations

def preprocess(words):
    #we'll make use of python's translate function,that maps one set of characters to another
    #we create an empty mapping table, the third argument allows us to list all of the characters
    #to remove during the translation process

    #first we will try to filter out some  unnecessary data like tabs
    table = str.maketrans('', '', '\t')
    words = [word.translate(table) for word in words]

    punctuations = (string.punctuation).replace("'", "")
    # the character: ' appears in a lot of stopwords and changes meaning of words if removed
    #hence it is removed from the list of symbols that are to be discarded from the documents
    trans_table = str.maketrans('', '', punctuations)
    stripped_words = [word.translate(trans_table) for word in words]

    #some white spaces may be added to the list of words, due to the translate function & nature of our documents
    #we remove them below
    words = [str for str in stripped_words if str]

    #some words are quoted in the documents & as we have not removed ' to maintain the integrity of some stopwords
    #we try to unquote such words below
    p_words = []
    for word in words:
        if (word[0] and word[len(word)-1] == "'"):
            word = word[1:len(word)-1]
        elif(word[0] == "'"):
            word = word[1:len(word)]
        else:
            word = word
        p_words.append(word)

    words = p_words.copy()

    #we will also remove just-numeric strings as they do not have any significant meaning in text classification
    words = [word for word in words if not word.isdigit()]

    #we will also remove single character strings
    words = [word for word in words if not len(word) == 1]

    #after removal of so many characters it may happen that some strings have become blank, we remove those
    words = [str for str in words if str]

    #we also normalize the cases of our words
    words = [word.lower() for word in words]

    #we try to remove words with only 2 characters
    words = [word for word in words if len(word) > 2]

    return words

#function to remove stopwords

def remove_stopwords(words):
    words = [word for word in words if not word in stopwords]
    return words
```

```
#function to convert a sentence into list of words

def tokenize_sentence(line):
    words = line[0:len(line)-1].strip().split(" ")
    words = preprocess(words)
    words = remove_stopwords(words)

    return words
```

```
#function to remove metadata

def remove_metadata(lines):
    start = 0  # Default to the beginning if no metadata is found
    for i in range(len(lines)):
        if lines[i] == '\n':  # Look for the first empty line
            start = i + 1
            break
    return lines[start:]  # Ensure start is always defined
```

```
from pathlib import Path

def tokenize(path):
    text = Path(path).read_text(encoding="utf-8", errors="ignore")  # Read entire file
    text_lines = text.split("\n")  # Split into lines
    text_lines = remove_metadata(text_lines)

    doc_words = []
    for line in text_lines:
        doc_words.append(tokenize_sentence(line))

    return doc_words
```

```
#a simple helper function to convert a 2D array to 1D, without using numpy

def flatten(list):
    new_list = []
    for i in list:
        for j in i:
            new_list.append(j)
    return new_list
```

## using the above functions on actual documents

```
len(folders)
```

```
20
```

```
from google.colab import drive
drive.flush_and_unmount()
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
list_of_words = []

for document in doc_train:
        list_of_words.append(flatten(tokenize(document)))
```

```
len(list_of_words)
```

```
14997
```

```
len(flatten(list_of_words))
```

```
2340356
```

from above lengths we observe that the code has been designed in as such a way that the 2D list: list_of_words contains the vocabulary of each document file in the each of its rows, and collectively contains all the words we extract from the 20_newsgroups folder

```
import numpy as np
np_list_of_words = np.asarray(flatten(list_of_words))
```

```
#finding the number of unique words that we have extracted from the documents

words, counts = np.unique(np_list_of_words, return_counts=True)
len(words)
```

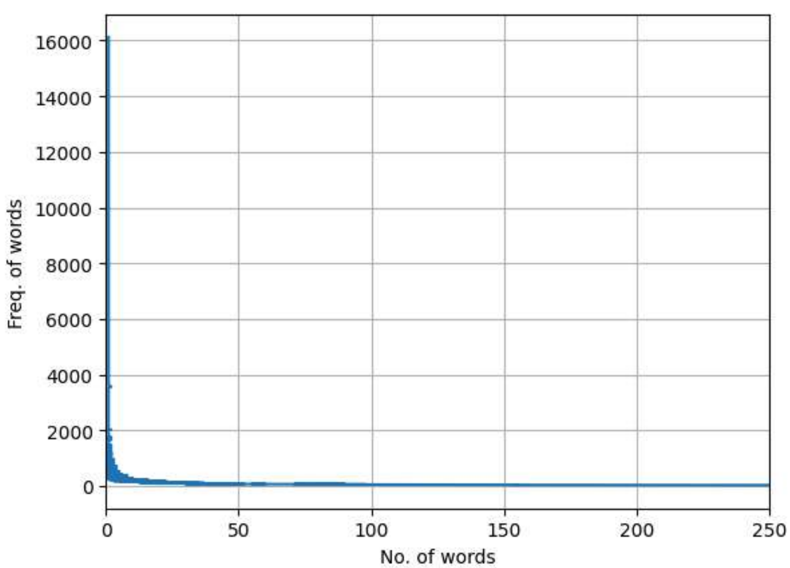
```
202190
```

```
#sorting the unique words according to their frequency

freq, wrds = (list(i) for i in zip(*(sorted(zip(counts, words), reverse=True))))
```

```
f_o_w = []
n_o_w = []
for f in sorted(np.unique(freq), reverse=True):
    f_o_w.append(f)
    n_o_w.append(freq.count(f))
```

```
import matplotlib.pyplot as plt
y = f_o_w
x = n_o_w
plt.xlim(0,250)
plt.xlabel("No. of words")
plt.ylabel("Freq. of words")
plt.plot(x, y)
plt.grid()
plt.show()
```




## we'll start making our train data here onwards

```
#deciding the no. of words to use as feature

n = 5000
features = wrds[0:n]
print(features)
```

```
['subject', 'lines', 'date', 'newsgroups', 'path', 'messageid', 'organization', 'apr', 'writes', 'references', 'article', 'sender', 'lik
```

```
#creating a dictionary that contains each document's vocabulary and ocurence of each word of the vocabulary

dictionary = {}
doc_num = 1
for doc_words in list_of_words:
    #print(doc_words)
    np_doc_words = np.asarray(doc_words)
    w, c = np.unique(np_doc_words, return_counts=True)
    dictionary[doc_num] = {}
    for i in range(len(w)):
        dictionary[doc_num][w[i]] = c[i]
    doc_num = doc_num + 1
```

```
dictionary.keys()
```

```
dict_keys([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32,
33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65,
66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98,
99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124,
125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150,
151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176,
177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202,
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671, 672, 673, 674, 675, 676, 677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 693, 694, 695, 696,
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749, 750, 751, 752, 753, 754, 755, 756, 757, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767, 768, 769, 770, 771, 772, 773, 774,
775, 776, 777, 778, 779, 780, 781, 782, 783, 784, 785, 786, 787, 788, 789, 790, 791, 792, 793, 794, 795, 796, 797, 798, 799, 800,
801, 802, 803, 804, 805, 806, 807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818, 819, 820, 821, 822, 823, 824, 825, 826,
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879, 880, 881, 882, 883, 884, 885, 886, 887, 888, 889, 890, 891, 892, 893, 894, 895, 896, 897, 898, 899, 900, 901, 902, 903, 904,
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931, 932, 933, 934, 935, 936, 937, 938, 939, 940, 941, 942, 943, 944, 945, 946, 947, 948, 949, 950, 951, 952, 953, 954, 955, 956,
957, 958, 959, 960, 961, 962, 963, 964, 965, 966, 967, 968, 969, 970, 971, 972, 973, 974, 975, 976, 977, 978, 979, 980, 981, 982,
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1184, 1185, 1186, 1187, 1188, 1189, 1190, 1191, 1192, 1193, 1194, 1195, 1196, 1197, 1198, 1199, 1200, 1201, 1202, 1203, 1204, 1205,
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1250, 1251, 1252, 1253, 1254, 1255, 1256, 1257, 1258, 1259, 1260, 1261, 1262, 1263, 1264, 1265, 1266, 1267, 1268, 1269, 1270, 1271,
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1294, 1295, 1296, 1297, 1298, 1299, 1300, 1301, 1302, 1303, 1304, 1305, 1306, 1307, 1308, 1309, 1310, 1311, 1312, 1313, 1314, 1315,
1316, 1317, 1318, 1319, 1320, 1321, 1322, 1323, 1324, 1325, 1326, 1327, 1328, 1329, 1330, 1331, 1332, 1333, 1334, 1335, 1336, 1337,
```

```
1338, 1339, 1340, 1341, 1342, 1343, 1344, 1345, 1346, 1347, 1348, 1349, 1350, 1351, 1352, 1353, 1354, 1355, 1356, 1357, 1358, 1359,
1360, 1361, 1362, 1363, 1364, 1365, 1366, 1367, 1368, 1369, 1370, 1371, 1372, 1373, 1374, 1375, 1376, 1377, 1378, 1379, 1380, 1381,
1382, 1383, 1384, 1385, 1386, 1387, 1388, 1389, 1390, 1391, 1392, 1393, 1394, 1395, 1396, 1397, 1398, 1399, 1400, 1401, 1402, 1403,
1404, 1405, 1406, 1407, 1408, 1409, 1410, 1411, 1412, 1413, 1414, 1415, 1416, 1417, 1418, 1419, 1420, 1421, 1422, 1423, 1424, 1425,
```

```
#now we make a 2D array having the frequency of each word of our feature set in each individual documents

X_train = []
for k in dictionary.keys():
    row = []
    for f in features:
        if(f in dictionary[k].keys()):
            #if word f is present in the dictionary of the document as a key, its value is copied
            #this gives us no. of occurences
            row.append(dictionary[k][f])
        else:
            #if not present, the no. of occurences is zero
            row.append(0)
    X_train.append(row)
```

```
#we convert the X and Y into np array for concatenation and conversion into dataframe

X_train = np.asarray(X_train)
Y_train = np.asarray(Y_train)
```

```
len(X_train)
```

```
14997
```

```
len(Y_train)
```

```
14997
```

## we'll make our test data by performing the same operations as we did for train data

```
list_of_words_test = []

for document in doc_test:
        list_of_words_test.append(flatten(tokenize(document)))
```

```
dictionary_test = {}
doc_num = 1
for doc_words in list_of_words_test:
    #print(doc_words)
    np_doc_words = np.asarray(doc_words)
    w, c = np.unique(np_doc_words, return_counts=True)
    dictionary_test[doc_num] = {}
    for i in range(len(w)):
        dictionary_test[doc_num][w[i]] = c[i]
    doc_num = doc_num + 1
```

```
#now we make a 2D array having the frequency of each word of our feature set in each individual documents

X_test = []
for k in dictionary_test.keys():
    row = []
    for f in features:
        if(f in dictionary_test[k].keys()):
            #if word f is present in the dictionary of the document as a key, its value is copied
            #this gives us no. of occurences
            row.append(dictionary_test[k][f])
        else:
            #if not present, the no. of occurences is zero
            row.append(0)
    X_test.append(row)
```

```
X_test = np.asarray(X_test)
Y_test = np.asarray(Y_test)
```

```
len(X_test)
```

```
5000
```

```
len(Y_test)
```

```
5000
```

# Text Classification

## performing Text Classification using sklearn's Multinomial Naive Bayes

```
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB()
clf.fit(X_train, Y_train)
```

```
▾ MultinomialNB
MultinomialNB()
```

```
Y_predict = clf.predict(X_test)
```

### testing scores

```
clf.score(X_test, Y_test)
```

```
0.8642
```

```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(classification_report(Y_test, Y_predict))
```

```
                          precision    recall  f1-score   support

             alt.atheism       0.71      0.86      0.78       240
           comp.graphics       0.79      0.85      0.82       247
 comp.os.ms-windows.misc       0.85      0.83      0.84       234
comp.sys.ibm.pc.hardware       0.81      0.80      0.81       232
   comp.sys.mac.hardware       0.87      0.92      0.89       243
          comp.windows.x       0.92      0.91      0.91       257
            misc.forsale       0.76      0.91      0.83       236
               rec.autos       0.87      0.90      0.89       245
         rec.motorcycles       0.92      0.96      0.94       249
      rec.sport.baseball       0.98      0.99      0.98       281
        rec.sport.hockey       0.99      0.97      0.98       259
               sci.crypt       0.96      0.94      0.95       253
         sci.electronics       0.87      0.85      0.86       253
                 sci.med       0.94      0.85      0.90       233
```

```
               sci.space       0.92      0.88      0.90       239
  soc.religion.christian       0.93      0.98      0.96       248
      talk.politics.guns       0.78      0.90      0.83       260
   talk.politics.mideast       0.93      0.89      0.91       237
      talk.politics.misc       0.73      0.67      0.70       271
      talk.religion.misc       0.76      0.46      0.57       283

                accuracy                           0.86      5000
               macro avg       0.87      0.87      0.86      5000
            weighted avg       0.87      0.86      0.86      5000
```

## training scores

```
Y_predict_tr = clf.predict(X_train)
```

```
clf.score(X_train, Y_train)
```

```
0.9159831966393278
```

```
print(classification_report(Y_train, Y_predict_tr))
```

```
                          precision    recall  f1-score   support

             alt.atheism       0.81      0.91      0.86       760
           comp.graphics       0.86      0.91      0.88       753
 comp.os.ms-windows.misc       0.91      0.92      0.92       766
comp.sys.ibm.pc.hardware       0.91      0.93      0.92       768
   comp.sys.mac.hardware       0.94      0.96      0.95       757
          comp.windows.x       0.97      0.92      0.94       743
            misc.forsale       0.85      0.94      0.90       764
               rec.autos       0.94      0.96      0.95       755
         rec.motorcycles       0.95      0.98      0.97       751
      rec.sport.baseball       0.98      0.99      0.99       719
        rec.sport.hockey       0.99      0.99      0.99       741
               sci.crypt       0.98      0.93      0.96       747
         sci.electronics       0.93      0.93      0.93       747
                 sci.med       0.97      0.93      0.95       767
               sci.space       0.97      0.95      0.96       761
  soc.religion.christian       0.97      0.99      0.98       749
      talk.politics.guns       0.82      0.95      0.88       740
   talk.politics.mideast       0.95      0.90      0.92       763
      talk.politics.misc       0.82      0.74      0.77       729
      talk.religion.misc       0.80      0.58      0.67       717

                accuracy                           0.92     14997
               macro avg       0.92      0.92      0.91     14997
            weighted avg       0.92      0.92      0.91     14997
```

# performing Text Classification using my implementation of Multinomial Naive Bayes

## functions for my implementation

```
#function to create a training dictionary out of the text files for training set, consisiting the frequency of
#words in our feature set (vocabulary) in each class or label of the 20 newsgroup

def fit(X_train, Y_train):
    result = {}
    classes, counts = np.unique(Y_train, return_counts=True)

    for i in range(len(classes)):
        curr_class = classes[i]

        result["TOTAL_DATA"] = len(Y_train)
        result[curr_class] = {}

        X_tr_curr = X_train[Y_train == curr_class]

        num_features = n

        for j in range(num_features):
            result[curr_class][features[j]] = X_tr_curr[:,j].sum()

        result[curr_class]["TOTAL_COUNT"] = counts[i]

    return result


#function for calculating naive bayesian log probablity for each test document being in a particular class

def log_probablity(dictionary_train, x, curr_class):
    output = np.log(dictionary_train[curr_class]["TOTAL_COUNT"]) - np.log(dictionary_train["TOTAL_DATA"])
    num_words = len(x)
    for j in range(num_words):
        if(x[j] in dictionary_train[curr_class].keys()):
            xj = x[j]
            count_curr_class_equal_xj = dictionary_train[curr_class][xj] + 1
            count_curr_class = dictionary_train[curr_class]["TOTAL_COUNT"] + len(dictionary_train[curr_class].keys(
            curr_xj_prob = np.log(count_curr_class_equal_xj) - np.log(count_curr_class)
            output = output + curr_xj_prob
        else:
            continue

    return output


#helper function for the predict() function that predicts the class or label for one test document at a time

def predictSinglePoint(dictionary_train, x):
    classes = dictionary_train.keys()
    best_p = -10000
    best_class = -1
    for curr_class in classes:
        if(curr_class == "TOTAL_DATA"):
            continue
        p_curr_class = log_probablity(dictionary_train, x, curr_class)
        if(p_curr_class > best_p):
            best_p = p_curr_class
            best_class = curr_class

    return best_class
```

```
#predict function that predicts the class or label of test documents using train dictionary made using the fit() fu

def predict(dictionary_train, X_test):
    Y_pred = []
    for x in X_test:
        y_predicted = predictSinglePoint(dictionary_train, x)
        Y_pred.append(y_predicted)

    #print(Y_pred)
    return Y_pred
```

## performing the implementation

```
train_dictionary = fit(X_train, Y_train)
```

```
X_test = []

for key in dictionary_test.keys():
    X_test.append(list(dictionary_test[key].keys()))
```

```
my_predictions = predict(train_dictionary, X_test)
```

```
my_predictions = np.asarray(my_predictions)
```

```
accuracy_score(Y_test, my_predictions)
```

```
0.7434
```

```
print(classification_report(Y_test, my_predictions))
```

```
                          precision    recall  f1-score   support

             alt.atheism       0.69      0.83      0.76       240
           comp.graphics       0.78      0.81      0.80       247
 comp.os.ms-windows.misc       0.94      0.63      0.76       234
comp.sys.ibm.pc.hardware       0.84      0.68      0.75       232
   comp.sys.mac.hardware       0.95      0.83      0.88       243
          comp.windows.x       0.84      0.88      0.86       257
            misc.forsale       0.94      0.58      0.72       236
               rec.autos       0.96      0.58      0.72       245
         rec.motorcycles       1.00      0.63      0.77       249
      rec.sport.baseball       1.00      0.80      0.89       281
        rec.sport.hockey       1.00      0.90      0.95       259
               sci.crypt       0.69      0.91      0.78       253
         sci.electronics       0.90      0.60      0.72       253
                 sci.med       0.92      0.78      0.84       233
               sci.space       0.89      0.78      0.83       239
  soc.religion.christian       0.91      0.97      0.94       248
      talk.politics.guns       0.93      0.66      0.77       260
   talk.politics.mideast       0.30      0.98      0.46       237
      talk.politics.misc       0.44      0.78      0.56       271
      talk.religion.misc       0.79      0.30      0.43       283

                accuracy                           0.74      5000
               macro avg       0.84      0.75      0.76      5000
            weighted avg       0.84      0.74      0.76      5000
```

```
print(type(X_test))  # Should be a list or NumPy array
print(len(X_test))  # Number of samples
print(type(X_test[0]))  # Should be a list or NumPy array
print(X_test[0])  # Inspect the first sample
```

```
<class 'list'>
5000
<class 'list'>
['1qpetoinng45snoopycisufledu', '1qptphcf7accessdigexnet', 'access', 'accessdigexne', 'agenc', 'apr', 'army', 'ballistic', 'cantaloupesr
```

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Initialize the vectorizer
vectorizer = TfidfVectorizer(max_features=5000)  # Match feature size

# Fit on training data and transform both train & test sets
X_train = vectorizer.fit_transform(doc_train).toarray()
X_test = vectorizer.transform(doc_test).toarray()

# Verify new shape
print("X_train shape:", X_train.shape)  # Should be (num_samples, num_features)
print("X_test shape:", X_test.shape)    # Should match X_train shape
```

```
X_train shape: (14997, 5000)
```