Out[7]:

age	job	marital	education	housing	loan	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	Product_
56	0	1	1	0	0	261	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
57	2	1	0	0	0	149	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
37	2	1	0	1	0	226	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
40	2	1	1	0	0	151	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
56	2	1	0	0	1	307	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
45	2	1	1	0	0	198	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
59	2	1	1	0	0	139	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
41	1	1	0	0	0	217	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
24	2	0	1	1	0	380	1	999	0	1.1	93.994	-36.4	4.857	5191.0	
25	2	0	0	1	0	50	1	999	0	1.1	93.994	-36.4	4.857	5191.0	

Out[11]:

```
MLPClassifier(activation='logistic', alpha=0.0001, batch_size='auto',
       beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(200, 150, 100), learning_rate='constant',
       learning_rate_init=0.0001, max_iter=1000000, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=None, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=False, warm_start=False)
```

In [12]:

```
pred = clf.predict(X_test)
print('Accuracy = ', metrics.accuracy_score(y_test, pred)*100, '%')
print('Recall Score = ',metrics.recall_score(y_test, pred))
print('Precision = ',metrics.precision_score(y_test, pred))
print('Confusion matrix : \n',metrics.confusion_matrix(y_test, pred))
```

```
Accuracy =  90.99737787705156 %
Recall Score =  0.44341994970662196
Precision =  0.6679292929292929
Confusion matrix :
 [[8841  263]
 [ 664  529]]
```

```
Classes in the dataset are :  ['tech', 'entertainment', 'politics', 'business', 'sport']
```

```
The train and test sizes are 1590 and 635 respectively
```

```
Vocabulary created consisting of : 26180 words

 ['aa', 'aaa', 'aaas', 'aac', 'aadc', 'aaliyah', 'aaltra', 'aamir', 'aan', 'aaron', 'aashare', 'abacus', 'abandon', 'abandone
d', 'abandoning', 'abandonment', 'abate', 'abatement', 'abating', 'abba', 'abbas', 'abbasi', 'abbot', 'abbott', 'abbreviate
d', 'abc', 'abd', 'abdellatif', 'abdication', 'abdomen', 'abdominal', 'abdul', 'abdullah', 'abdullatif', 'abebe', 'abensur',
'aberavon', 'aberdeen', 'aberdeenbased', 'aberration', 'aberystwyth', 'abeyance', 'abeyie', 'abhorrent', 'abi', 'abide', 'abi
ded', 'abiding', 'abigail', 'abilities', 'ability', 'abishuly', 'abiyote', 'able', 'ablebodied', 'abn', 'abnormal', 'abnormal
ity', 'abolish', 'abolished', 'abolishing', 'abortion', 'abortionist', 'abortions', 'abortive', 'about', 'aboutroughly', 'abo
ve', 'aboveaverage', 'abraham', 'abramovich', 'abroad', 'abruptly', 'absa', 'absence', 'absences', 'absent', 'absentee', 'abs
olute', 'absolutely', 'absorb', 'absorbed', 'absorbing', 'absorbs', 'abstain', 'abstentions', 'abstract', 'absurd', 'abtahi',
'abu', 'abundance', 'abundantly', 'aburizal', 'abuse', 'abused', 'abusers', 'abuses', 'abusing', 'abusive', 'abut', 'abysma
l', 'ac', 'academia', 'academic', 'academically', 'academics', 'academy', 'acapulco', 'acasuso', 'accelerate', 'accelerated',
'accelerating', 'acceleration', 'accelerator', 'accent', 'accept', 'acceptable', 'acceptance', 'accepted', 'accepting', 'acce
pts', 'access', 'accessed', 'accessibility', 'accessible', 'accessing', 'accession', 'accessories', 'accessory', 'accident',
'accidental', 'accidentally', 'accidently', 'accidents', 'acclaim', 'acclaimed', 'acclimate', 'accolade', 'accolades', 'accom
modate', 'accommodation', 'accomodate', 'accompanied', 'accompanies', 'accompany', 'accompanying', 'accomplice', 'accomplice
s', 'accomplish', 'accomplished', 'accomplishment', 'accord', 'accordance', 'according', 'accordingly', 'accosiation', 'accou
nt', 'accountability', 'accountable', 'accountancy', 'accountant', 'accountants', 'accounted', 'accounting', 'accounts', 'acc
oustic', 'accrued', 'accumulate', 'accumulated', 'accumulates', 'accumulation', 'accumulator', 'accura', 'accuracy', 'accurat
e', 'accurately', 'accusations', 'accuse', 'accused', 'accuser', 'accusers', 'accuses', 'accusing', 'accustomed', 'ace', 'ace
```

```
Bag of words representation :
       aa  aaa  aaas  aac  aadc  aaliyah  aaltra  aamir  aan  aaron  \
0       0    0     0    0     0        0       0      0    0      0
1       0    0     0    0     0        0       0      0    0      0
2       0    0     0    0     0        0       0      0    0      0
3       0    0     0    0     0        0       0      0    0      0
4       0    0     0    0     0        0       0      0    0      0
5       0    0     0    0     0        0       0      0    0      0
6       0    0     0    0     0        0       0      0    0      0
7       0    0     0    0     0        0       0      0    0      0
8       0    0     0    0     0        0       0      0    0      0
9       0    0     0    0     0        0       0      0    0      0
10      0    0     0    0     0        0       0      0    0      0
11      0    0     0    0     0        0       0      0    0      0
12      0    0     0    0     0        0       0      0    0      0
13      0    0     0    0     0        0       0      0    0      0
14      0    0     0    0     0        0       0      0    0      0
15      0    0     0    0     0        0       0      0    0      0
16      0    0     0    0     0        0       0      0    0      0
17      0    0     0    0     0        0       0      0    0      0
```

```
         ...       zones  zoom  zooropa  zorro  zubair  zuluaga  zurich  \
0        ...           0     0        0      0       0        0       0
1        ...           0     0        0      0       0        0       0
2        ...           0     0        0      0       0        0       0
3        ...           0     0        0      0       0        0       0
4        ...           0     0        0      0       0        0       0
5        ...           0     0        0      0       0        0       0
6        ...           0     0        0      0       0        0       0
7        ...           0     0        0      0       0        0       0
8        ...           0     0        0      0       0        0       0
9        ...           0     0        0      0       0        0       0
10       ...           0     0        0      0       0        0       0
11       ...           0     0        0      0       0        0       0
12       ...           0     0        0      0       0        0       0
13       ...           0     0        0      0       0        0       0
14       ...           0     0        0      0       0        0       0
15       ...           0     0        0      0       0        0       0
16       ...           0     0        0      0       0        0       0
17       ...           0     0        0      0       0        0       0
```

```
Accuracy of algorithm =  96.69291338582677 %
Confusion matrix :
[[117   1   1   0   0]
 [  4 101   4   0   0]
 [  0   0 120   0   0]
 [  5   1   5 135   0]
 [  0   0   0   0 141]]


Other accuracy measures :
              precision    recall  f1-score   support

           0       0.93      0.98      0.96       119
           1       0.98      0.93      0.95       109
           2       0.92      1.00      0.96       120
           3       1.00      0.92      0.96       146
           4       1.00      1.00      1.00       141

   micro avg       0.97      0.97      0.97       635
   macro avg       0.97      0.97      0.97       635
weighted avg       0.97      0.97      0.97       635
```

Out[12]:

	text
0	chelsea sack mutu chelsea have sacked adrian ...
1	set your television to wow television started...
2	russian film wins bbc world prize russian dra...
3	markets signal brazilian recovery the brazili...
4	iraqis win death test case probe the family o...
5	apple ipod family expands market apple has ex...

In [13]:

```
newdoc_dtm = DocVector.transform(newdoc.text)
newpredict = MNBayes.predict(newdoc_dtm)
preddoc = list()
for i in range(len(newdoc)):
    preddoc.append([newdoc.text[i], revclassdict[newpredict[i]]])
pd.DataFrame(preddoc, columns=['text', 'predicted class'])
```

Out[13]:

	text	predicted class
0	chelsea sack mutu chelsea have sacked adrian ...	sport
1	set your television to wow television started...	tech
2	russian film wins bbc world prize russian dra...	entertainment
3	markets signal brazilian recovery the brazili...	business
4	iraqis win death test case probe the family o...	politics
5	apple ipod family expands market apple has ex...	tech