In [1]:

```
#import important libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# import libraries for EDA and preprocessing
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
nltk.download('wordnet')
from nltk.stem import WordNetLemmatizer

# import libraries for modeling
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF
from sklearn.metrics import accuracy_score
import sklearn.metrics as metrics
import itertools
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# import libraries for evaluating
from sklearn.metrics import confusion_matrix
import time
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/linhtran/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/linhtran/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

We have BBC News Train and BBC News Test data downloaded from Kaggle which consists of 5 categories in total. And the goal is to assign one category to a news article in test data. The five categories we want to identify are Sports, Business, Politics, Tech, and Entertainment.

To do this, we will train two models:
(1) an unsupervised model using matrix factorization
(2) a supervised model using KMeans clustering.
Both models are built to have their testing accuracy and then I will compare these two models for their performance.

Step 1: Inspect, Visualize and Clean the Data

In [2]:

```
# read data
train_df = pd.read_csv('BBC News Train.csv')
```

In [3]:

```
# read data
test_df = pd.read_csv('BBC News Test.csv')
```

In [4]:
```
# take a look at some rows of train data
train_df.head()
```

Out[4]:

	ArticleId	Text	Category
0	1833	worldcom ex-boss launches defence lawyers defe...	business
1	154	german business confidence slides german busin...	business
2	1101	bbc poll indicates economic gloom citizens in ...	business
3	1976	lifestyle governs mobile choice faster bett...	tech
4	917	enron bosses in $168m payout eighteen former e...	business

In [5]:
```
# the shape of train data
train_df.shape
```

Out[5]:
```
(1490, 3)
```

In [6]:
```
# get a quick description of the data
train_df.describe()
```

Out[6]:

	ArticleId
count	1490.000000
mean	1119.696644
std	641.826283
min	2.000000
25%	565.250000
50%	1112.500000
75%	1680.750000
max	2224.000000

In [7]:
```
# the structure of data also tells us the number of rows (observations) and colu
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1490 entries, 0 to 1489
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ArticleId  1490 non-null   int64
 1   Text       1490 non-null   object
 2   Category   1490 non-null   object
dtypes: int64(1), object(2)
memory usage: 35.0+ KB
```

In [8]:
```
# get the category of train data
train_df['Category'].unique()
```

Out[8]:
```
array(['business', 'tech', 'politics', 'sport', 'entertainment'],
      dtype=object)
```

In [9]:
```
# check null values in train data
train_df.isnull().sum()
```

Out[9]:
```
ArticleId    0
Text         0
Category     0
dtype: int64
```

In [10]:
```
# check for duplicate articles
train_df.duplicated(keep=False).sum()
```

Out[10]:
```
0
```

From the output above, we can summarize that:

- There are 1490 rows and 3 columns in train data.
- There are five categories in train data, include 'business', 'tech', 'politics', 'sport' and 'entertainment'.
- There is no missing values.
- There is one integer column and it is Article ID.
- There are two object columns, they are Text and Category.
- There is no duplicate articles.

  Next, I will calculate and visualize the count and the proportion of each label in train data.

In [11]:
```
# calculate the count of each label
train_df['Category'].value_counts()
```

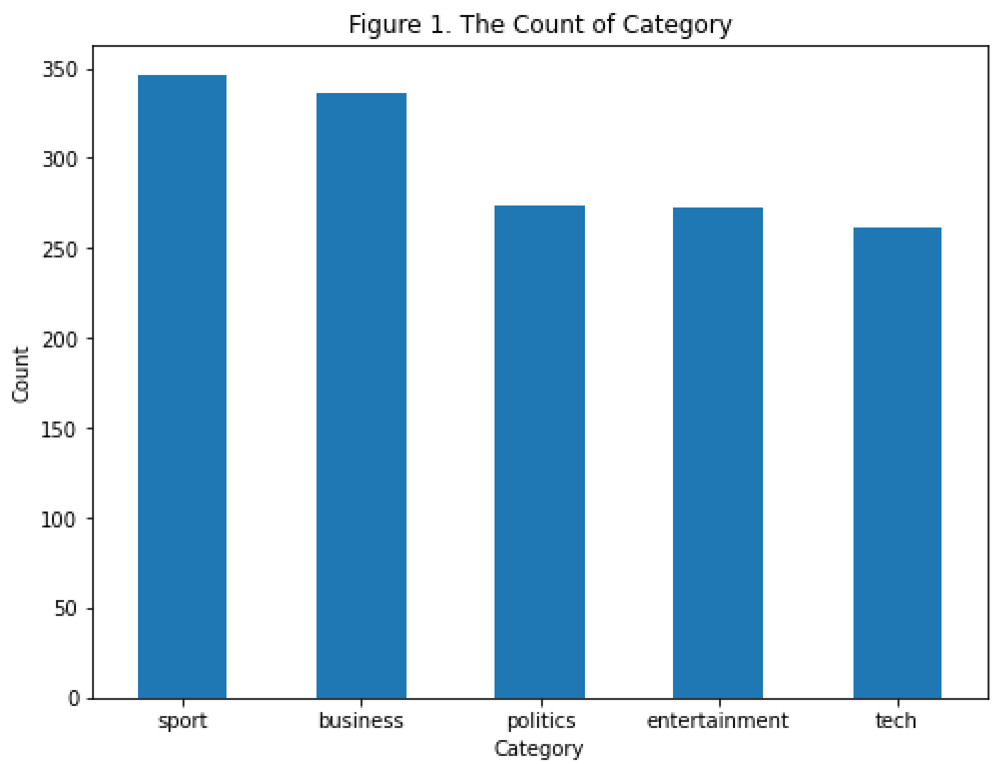
Out[11]:
```
sport            346
business         336
politics         274
entertainment    273
tech             261
Name: Category, dtype: int64
```

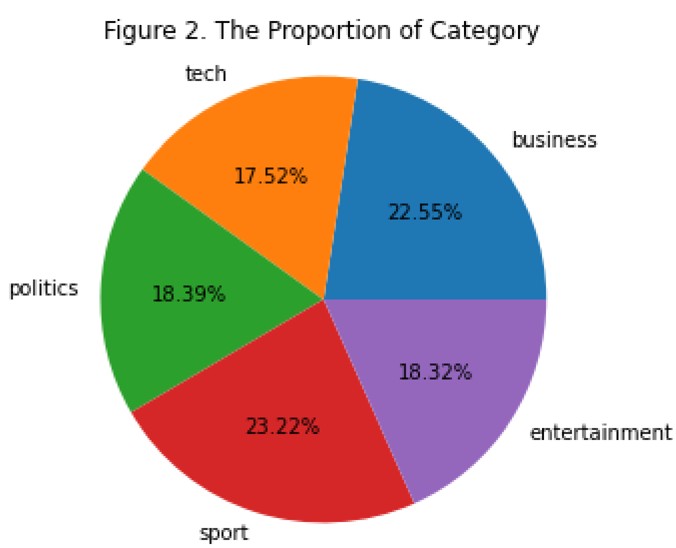
In [12]:
```
# calculate the proportion of each label
train_df['Category'].value_counts()/len(train_df)*100
```

Out[12]:
```
sport            23.221477
business         22.550336
politics         18.389262
entertainment    18.322148
tech             17.516779
Name: Category, dtype: float64
```

In [13]:
```
# plot the count of each category
fig, ax = plt.subplots(figsize=(8,6))
train_df['Category'].value_counts().plot(kind='bar', ax=ax)
plt.xlabel("Category")
plt.xticks(rotation=360)
```

```
plt.ylabel("Count")
plt.title("Figure 1. The Count of Category")

# plot the proportion of each category
labels = train_df['Category'].unique().tolist()
counts = train_df['Category'].value_counts()
sizes = [counts[v] for v in labels]
fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%0.2f%%')
ax1.axis('equal')
plt.title("Figure 2. The Proportion of Category")

plt.tight_layout()
plt.show()
```





Looking at Figure 2, we can see the proportions of each kind of article. In overall, the number of article for each category is not different too much. I think this is good since if one or two categories was severely underrepresentated or, in contrast, overrepresentative in the train data, then it may cause our model to be biased and/or perform poorly on some or all of the test data.

To preprocess our text simply means to bring our text into a form that is predictable and analyzable for our task. So, what I am going to do is:
(1) lowercasing all our text data
(2) remove punctuation
(3) remove stop words: stop words are a set of commonly used words in a language. Examples of stop words in English are “a”, “the”, “is”, “are” and etc. The intuition behind using stop words is that, by removing low information words from text, we can focus on the important words instead.
(4) lemmatization: lemmatization usually refers to doing things properly with the use of a vocabulary and morphological analysis of words, normally aiming to remove inflectional endings only and to return the base or dictionary form of a word, which is known as the lemma. For example, runs, running, ran are all forms of the word run, therefore run is the lemma of all these words.

Because I will redo these cleaning steps for test data as well, thus for convenience, I will create a clean_text function for train data and reuse it for cleaning test data later.

In [14]:
```
def clean_text(data, text):
    # lowercasing all text data
    data[text] = data[text].str.lower()
    # remove punctuation
    data[text] = data[text].str.replace('[^\w\s]', '', regex=True)
    # remove stop words
    stop_words = stopwords.words('english')
    data[text] = data[text].apply(lambda x: ' '.join([word for word in x.split()
    # lemmatization
    lemmatizer = WordNetLemmatizer()
    data[text] = data[text].apply(lambda x: ' '.join([lemmatizer.lemmatize(word)
    return
```

In [15]:
```
# clean train data
clean_text(train_df, "Text")

# view text in the first row after cleaning all text data
train_df["Text"][0]
```

Out[15]:
```
'worldcom exboss launch defence lawyer defending former worldcom chief bernie eb
bers battery fraud charge called company whistleblower first witness cynthia coo
per worldcom exhead internal accounting alerted director irregular accounting pr
actice u telecom giant 2002 warning led collapse firm following discovery 11bn 5
7bn accounting fraud mr ebbers pleaded guilty charge fraud conspiracy prosecutio
n lawyer argued mr ebbers orchestrated series accounting trick worldcom ordering
employee hide expense inflate revenue meet wall street earnings estimate m coope
r run consulting business told jury new york wednesday external auditor arthur a
ndersen approved worldcom accounting early 2001 2002 said andersen given green l
ight procedure practice used worldcom mr ebber lawyer said unaware fraud arguing
auditor alert problem m cooper also said shareholder meeting mr ebbers often pas
sed technical question company finance chief giving brief answer prosecution sta
r witness former worldcom financial chief scott sullivan said mr ebbers ordered
```

```
accounting adjustment firm telling hit book however m cooper said mr sullivan me
ntioned anything uncomfortable worldcom accounting 2001 audit committee meeting
mr ebbers could face jail sentence 85 year convicted charge facing worldcom emer
ged bankruptcy protection 2004 known mci last week mci agreed buyout verizon com
munication deal valued 675bn'
```

In [16]:

```
# calculate the count of word per article
train_df["Word_Count"] = train_df['Text'].apply(lambda x: len(x.split()))
```

In [17]:

```
# view some first rows of train data
train_df.head()
```

Out[17]:

	ArticleId	Text	Category	Word_Count
0	1833	worldcom exboss launch defence lawyer defendin...	business	191
1	154	german business confidence slide german busine...	business	203
2	1101	bbc poll indicates economic gloom citizen majo...	business	292
3	1976	lifestyle governs mobile choice faster better ...	tech	353
4	917	enron boss 168m payout eighteen former enron d...	business	211

In [18]:

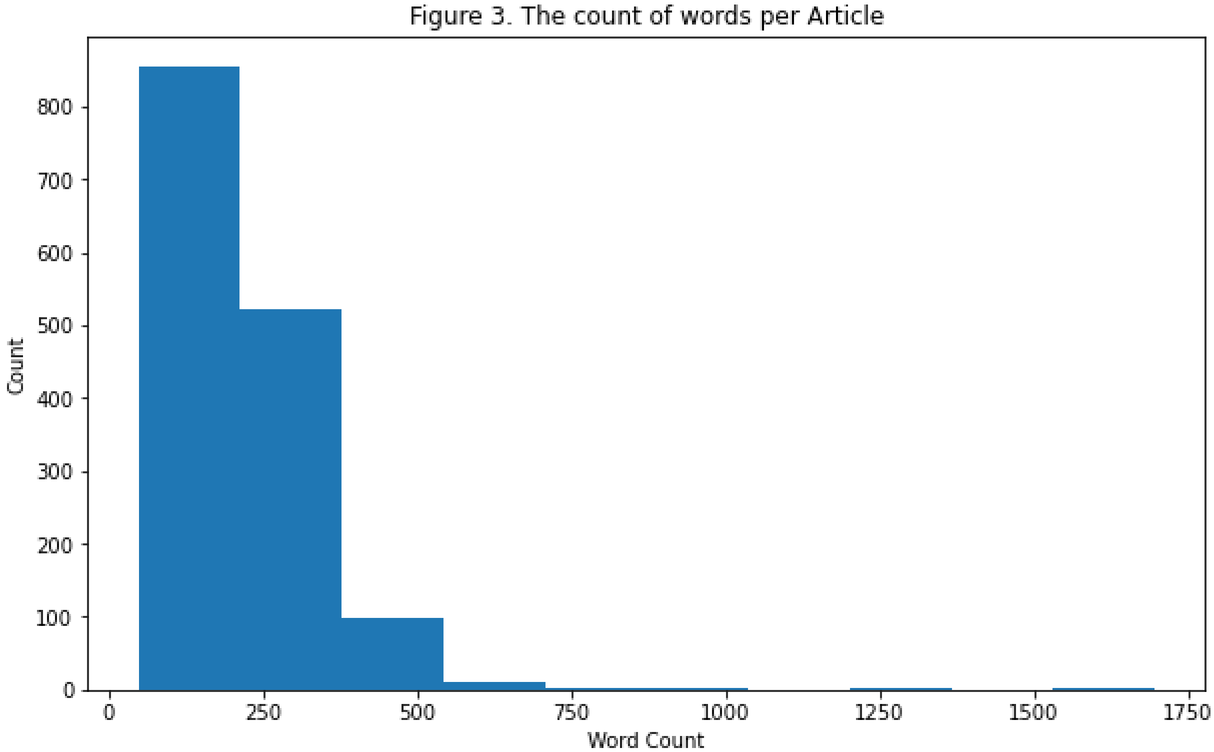
```
# The average count of word per article
np.mean(train_df.Word_Count)
```

Out[18]:

```
219.6469798657718
```

In [19]:

```
# plot the count of word per article
fig, ax = plt.subplots(figsize=(10,6))
train_df['Word_Count'].plot(kind='hist')
plt.xlabel("Word Count")
plt.xticks(rotation=360)
plt.ylabel("Count")
plt.title("Figure 3. The count of words per Article")
plt.show()
```



We see that the average count of words per article is about 220 and looking at Figure 3, there are some outliers that have over 750 word count per article. Thus, I would like to remove articles that have more than 750 words. And then I will plot the count of words per category.

In [20]:

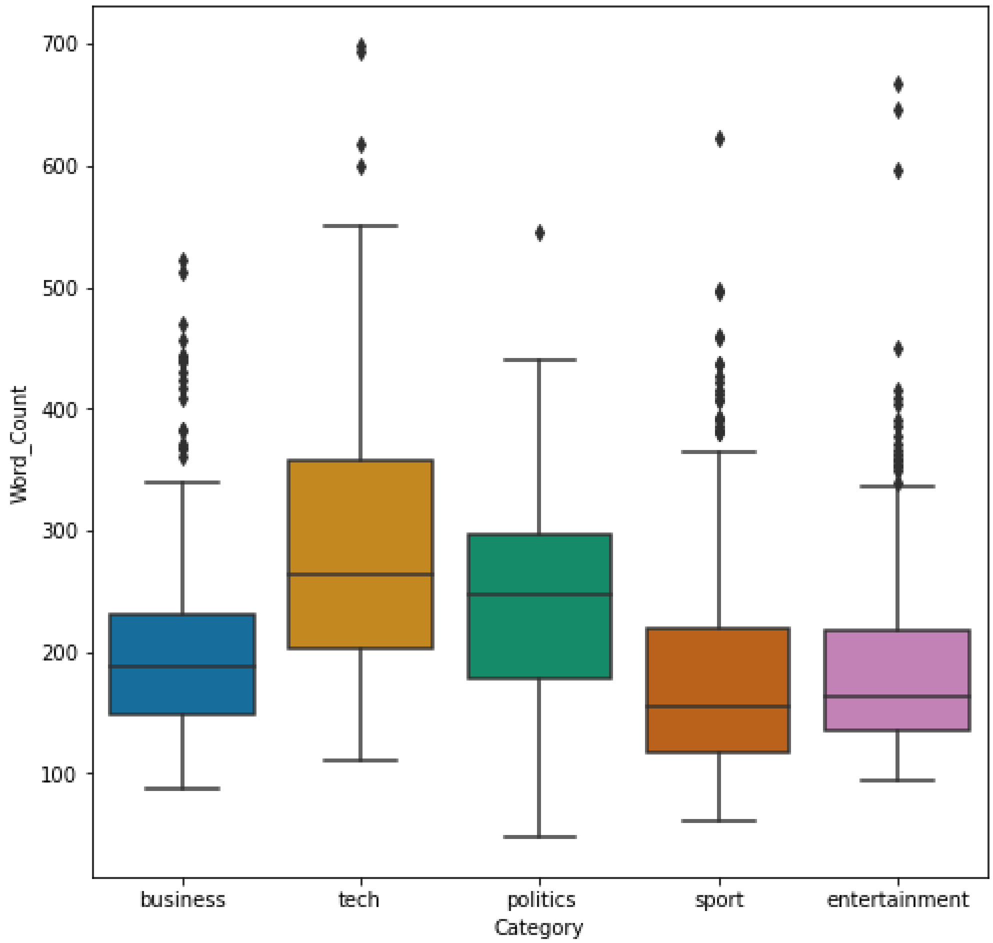
```
# remove outliers have more than 750 words
train_df = train_df[train_df.Word_Count <= 750]
len(train_df)
```

Out[20]: 1484

In [21]:

```
# visualize the count of words per category
fig, ax = plt.subplots(figsize=(8, 8))
sns.boxplot(data = train_df, x = 'Category', y = 'Word_Count', palette = 'colorb
            ).set(title = 'Figure 4. The count of words per Category')
plt.show()
```

Figure 4. The count of words per Category



Looking at Figure 4, we observe that the mean of word count of each category is not different much, tech and politics have more words and variance than business, sport and entertainment.

Split data

After cleaning, to prepare for building and training models, we split 20% of the data into a separate cross validation dataset, keeping the same proportion of classes in each subset.

In [22]:

```
train, crossval = train_test_split(train_df.drop(columns='Word_Count'), test_siz
print('Training set:')
train. head()
```

```
Training set:
```

Out[22]:

	ArticleId	Text	Category
384	674	msps hear renewed climate warning climate chan...	politics
536	286	nissan name successor ghosn nissan named lifet...	business
678	581	napster offer rented music go music downloadin...	tech
486	2021	ad sale boost time warner profit quarterly pro...	business
408	1483	youssou n dour win music prize senegalese musi...	entertainment

In [23]:

```
# get shape of train dataset after splitting
train.shape
```

Out[23]: (1187, 3)

In [24]:
```
print('Cross validation set:')
crossval.head()
```

Cross validation set:

Out[24]:

	ArticleId	Text	Category
124	1091	smart search let art fan browse know art know ...	tech
435	2175	lifestyle governs mobile choice faster better ...	tech
1037	856	japan bank share link talk share sumitomo mits...	business
533	1468	commodore find new lease life oncefamous commo...	tech
1423	7	blair prepares name poll date tony blair likel...	politics

In [25]:
```
# get shape of cross validation dataset after splitting
crossval.shape
```

Out[25]: (297, 3)

Step 2: Building and training models

Machines, unlike humans, cannot understand the raw text. Machines can only see numbers. Particularly, statistical techniques such as machine learning can only deal with numbers. Therefore, we need to convert our text into numbers (vectors) so as the algorithms will be able make predictions.

Different approaches exist to convert text into the corresponding numerical form. In this case I will use the Term Frequency — Inverse Document Frequency (TFIDF) weight to evaluate how important a word is to a document in a collection of documents. Note that we are passing a number of parameters to this work:

- min_df is used for removing terms that appear too infrequently, set to 0.002 means "ignore terms that appear in less than 0.2% of the documents". This is to avoid rare words, which drastically increase the size of our features and might cause overfitting.
- max_df is used for removing terms that appear too frequently, set to 0.95 means "ignore terms that appear in more than 95% of the documents".
- norm is set to l2, to ensure all our feature vectors have a euclidian norm of 1. This is helpful for visualizing these vectors, and can also improve (or deteriorate) the performance of some models.
- ngram_range is set to (1, 2) to indicate that we want to consider both unigrams and bigrams, or in other terms: we want to consider single words ("prices", "player") and pairs of words ("stock prices", "football player").
- stop_words is set to "english" to remove all common pronouns ("a", "the", ...) and further reduce the number of noisy features.

- sublinear_df is set to True to use a logarithmic form for frequency, to give diminishing returns as the frequency of a word increases.

In [26]:
```
# use IFIDF to convert words into numerical features
vectorizer = TfidfVectorizer(min_df=0.002, max_df=0.95, norm='l2', ngram_range=(
X = vectorizer.fit_transform(train.Text)
```

In [27]:
```
# Get a feel of the features identified by tfidf
X.toarray()
```

Out[27]:
```
array([[0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.04042066, ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.03212369, ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.        , 0.        , 0.03232147, ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.03519229, ..., 0.        , 0.        ,
        0.        ]])
```

In [28]:
```
# get the shape of the features
X.shape
```

Out[28]:
```
(1187, 15020)
```

Next, I'll build Non-Negative Matrix Factorization (NMF) model. First, I'm just passing a number of parameters to this model by default, except for n_components=5, because we have 5 topics.

In [29]:
```
#create model
nmf_model = NMF(n_components=5,
                init=None,
                solver = 'cd',
                beta_loss = 'frobenius',
                random_state = 42)

# fit and transform the model to TF-IDF:
W = nmf_model.fit_transform(X)
H = nmf_model.components_
```

In [30]:
```
# features dimension
W.shape
```

Out[30]:
```
(1187, 5)
```

In [31]:
```
# components dimension
H.shape
```

Out[31]: (5, 15020)

In [32]:

```
# Create a DataFrame: components_df
components_df = pd.DataFrame(H, columns=vectorizer.get_feature_names())
components_df
```

Out[32]:

	00	00 draw	000	000 amicus	000 balloted	000 barrel	000 business	000 car	000 complaint
0	0.000000	0.000515	0.127216	0.000000	0.000000	0.000000	0.000893	0.001538	0.006656
1	0.014613	0.008882	0.017295	0.000000	0.000000	0.000000	0.000000	0.000000	0.000313
2	0.001530	0.000000	0.066593	0.003640	0.003640	0.000000	0.003314	0.000000	0.000785
3	0.000000	0.000000	0.036131	0.000000	0.000000	0.000000	0.000000	0.000000	0.002122
4	0.000000	0.000000	0.080791	0.000157	0.000157	0.010749	0.002367	0.011482	0.000939

5 rows × 15020 columns

We have created the 5 topics using NMF. Let's have a look at the 10 more important words for each topic.

In [33]:

```
# get 10 more important words for each topic
for topic in range(components_df.shape[0]):
    tmp = components_df.iloc[topic]
    print(f'For topic {topic+1} the words with the highest value are:')
    print(tmp.nlargest(10))
    print('\n')
```

```
For topic 1 the words with the highest value are:
people        0.345764
user          0.311274
technology    0.302175
phone         0.272005
mobile        0.268877
digital       0.263531
service       0.259729
computer      0.252358
music         0.247690
software      0.246573
Name: 0, dtype: float64


For topic 2 the words with the highest value are:
game        0.347778
win         0.259950
player      0.255049
england     0.248411
match       0.243483
cup         0.217961
champion    0.210155
play        0.208086
injury      0.203786
team        0.202624
Name: 1, dtype: float64
```

```
For topic 3 the words with the highest value are:
mr                  0.353970
labour              0.343664
election            0.335550
party               0.296008
blair               0.287186
minister            0.267165
tory                0.266430
government          0.258987
prime minister      0.205558
prime               0.205421
Name: 2, dtype: float64


For topic 4 the words with the highest value are:
film            0.501122
award           0.385936
best            0.301244
actor           0.277695
star            0.252687
oscar           0.240120
actress         0.213038
nomination      0.184176
director        0.182146
comedy          0.170595
Name: 3, dtype: float64


For topic 5 the words with the highest value are:
market      0.240909
said        0.222460
company     0.216364
firm        0.211416
growth      0.201073
share       0.198104
year        0.195011
economy     0.185288
bank        0.183617
price       0.174149
Name: 4, dtype: float64
```

In [34]:

```
# create predict function
def predict(W):
    sortedW = np.argsort(W)
    n_prediction, maxValue = sortedW.shape
    prediction = [[sortedW[i][maxValue - 1]] for i in range(n_prediction)]
    topic = np.empty(n_prediction, dtype = np.int64)
    for i in range(n_prediction):
        topic[i] = prediction[i][0]
    return topic
```

In [35]:

```
# create label permuation compare
def label_permute_compare(ytdf,yp,n=5):
    """
```

```python
    ytdf: labels dataframe object
    yp: clustering label prediction output
    Returns permuted label order and accuracy.
    Example output: (3, 4, 1, 2, 0), 0.74
    """
    p = list(itertools.permutations(list(range(n))))
    label_ls = list(ytdf['Category'].unique())
    acc_score = []
    for i in range(len(p)):
        map_dict = dict(zip(label_ls, list(p[i])))
        yt = ytdf['Category'].apply(lambda x:map_dict[x])
        acc_score.append(accuracy_score(yt, yp))
    index = np.argmax(acc_score)
    return p[index], acc_score[index]
```

In [36]:

```python
# predict, show best labels for the train model and calculate accuracy
yhat_train = predict(W)
label_order, accuracy = label_permute_compare(train, yhat_train)
print('\nLabel order for training set based on NMF: ', label_order)
print('\nAccuracy for training set based on NMF: {:.3f}%'.format(accuracy*100))
```

```
Label order for training set based on NMF:  (2, 4, 0, 3, 1)

Accuracy for training set based on NMF: 94.861%
```

In [37]:

```python
# Check confusion matrix
mapdict = dict(zip(list(train["Category"].unique()), label_order))
yt = train["Category"].apply(lambda x: mapdict[x])
print('\nConfusion matrix for training set based on NMF: ')
confusion_matrix(yt, yhat_train)
```

```
Confusion matrix for training set based on NMF:
```

Out[37]:

```
array([[192,   6,   2,   3,   5],
       [  0, 264,   1,   2,   2],
       [  3,   0, 206,   0,   9],
       [ 10,   2,   1, 204,   8],
       [  2,   0,   5,   0, 260]])
```

In [38]:

```python
# predict, show best labels for the cross validatiion model and calculate accura
X_cross = vectorizer.fit_transform(crossval.Text)
W_cross = nmf_model.fit_transform(X_cross)
yhat_cross = predict(W_cross)
label_order_cross, accuracy_cross = label_permute_compare(crossval, yhat_cross)
print('\nLabel order for cross validation set based on NMF: ', label_order_cross
print('\nAccuracy for cross validation set based on NMF: {:.3f}%'.format(accurac
```

```
Label order for cross validation set based on NMF:  (3, 0, 1, 2, 4)

Accuracy for cross validation set based on NMF: 66.330%
```

In [39]:

```python
# Check confusion matrix
mapdict_cross = dict(zip(list(crossval["Category"].unique()), label_order_cross)
yt_cross = crossval["Category"].apply(lambda x: mapdict_cross[x])
print('\nConfusion matrix for cross validation set based on NMF: ')
confusion_matrix(yt_cross, yhat_cross)
```

```
Confusion matrix for cross validation set based on NMF:
```

Out[39]:
```
array([[68,  0,  1,  0,  0],
       [ 2, 49,  1,  0,  2],
       [ 0,  0, 75,  0,  0],
       [47,  0,  0,  5,  0],
       [22,  3, 17,  5,  0]])
```

Improve NMF model

Choosing the parameters for NMF model by default, we got a low accuracy score for the train and cross validation set. To improve the model, I'll programmatically evaluate which init, solver and beta_loss metric lead to the best performance and use this best model to predict on the test data.

In [40]:
```
# programmatically evaluate which init, solver and beta_loss metric lead to the
dic = {"time":0, "init":"", "solver": "", "beta_loss":"", "labelorder":[], "acc"
df = pd.DataFrame(dic)
for init in ["random", "nndsvda", "nndsvdar", "custom"]:
    for beta_loss in ["frobenius", "kullback-leibler", "itakura-saito"]:
        for solver in ["cd", "mu"]:
            acc = 0
            t0 = time.time()
            try:
                model = NMF(n_components=5, init=init, solver = solver, beta_los
                yhat_train = predict(model.fit_transform(X))
                label_order, acc = label_permute_compare(train, yhat_train)
                t1 = time.time()
                df.loc[len(df.index)] = [t1-t0, init, solver, beta_loss, label_o

            except:
                print(init, "with", beta_loss, "with", solver, "not allowed.")
df = df.sort_values(by='acc', ascending = False)
display(df)
```

```
random with kullback-leibler with cd not allowed.
random with itakura-saito with cd not allowed.
random with itakura-saito with mu not allowed.
nndsvda with kullback-leibler with cd not allowed.
nndsvda with itakura-saito with cd not allowed.
nndsvda with itakura-saito with mu not allowed.
nndsvdar with kullback-leibler with cd not allowed.
nndsvdar with itakura-saito with cd not allowed.
nndsvdar with itakura-saito with mu not allowed.
custom with frobenius with cd not allowed.
custom with frobenius with mu not allowed.
custom with kullback-leibler with cd not allowed.
custom with kullback-leibler with mu not allowed.
custom with itakura-saito with cd not allowed.
custom with itakura-saito with mu not allowed.
```

	time	init	solver	beta_loss	labelorder	acc
8	2.402451	nndsvdar	mu	kullback-leibler	(2, 4, 0, 3, 1)	0.962932
5	1.936520	nndsvda	mu	kullback-leibler	(2, 4, 0, 3, 1)	0.960404
1	0.198614	random	mu	frobenius	(1, 2, 0, 4, 3)	0.956192
3	0.198530	nndsvda	cd	frobenius	(2, 4, 0, 3, 1)	0.948610

	time	init	solver	beta_loss	labelorder	acc
6	0.211573	nndsvdar	cd	frobenius	(2, 4, 0, 3, 1)	0.948610
4	0.213634	nndsvda	mu	frobenius	(2, 4, 0, 3, 1)	0.941870
7	0.248036	nndsvdar	mu	frobenius	(2, 4, 0, 3, 1)	0.941028
0	0.161158	random	cd	frobenius	(3, 4, 0, 2, 1)	0.939343
2	3.138018	random	mu	kullback-leibler	(1, 2, 4, 0, 3)	0.696714

In [41]:

```
# show the best model
best_model = NMF(n_components=5, init="nndsvdar", solver = "mu", beta_loss="kull

# use best model for predicting training set
yhat_train = predict(best_model.fit_transform(X))
label_order, acc = label_permute_compare(train, yhat_train)
mapdict = dict(zip(list(train["Category"].unique()), label_order))
yt = train["Category"].apply(lambda x: mapdict[x])
print('\nLabel order for training set based on best NMF: ', label_order)
print('\nAccuracy for training set based on best NMF: {:.3f}%'.format(acc*100))
```

```
Label order for training set based on best NMF:  (2, 4, 0, 3, 1)

Accuracy for training set based on best NMF: 96.293%
```

In [42]:

```
# predict, show best labels for the cross validatiion model and calculate accura
W_cross = best_model.fit_transform(X_cross)
yhat_cross = predict(W_cross)
label_order_cross, accuracy_cross = label_permute_compare(crossval, yhat_cross)
print('\nLabel order for cross validation set based on best NMF: ', label_order_
print('\nAccuracy for cross validation set based on best NMF: {:.3f}%'.format(ac
```

```
Label order for cross validation set based on best NMF:  (4, 0, 1, 2, 3)

Accuracy for cross validation set based on best NMF: 67.677%
```

Use best model to predict test data

After finding the best model for our data, now we will test this model on the test set. Again, before predicting, we need to repeat the same steps to clean the test data like we did in the train data.

In [43]:

```
# take a look at some rows of test data
test_df.head()
```

Out[43]:

	ArticleId	Text
0	1018	qpr keeper day heads for preston queens park r...
1	1319	software watching while you work software that...
2	1138	d arcy injury adds to ireland woe gordon d arc...
3	459	india s reliance family feud heats up the ongo...
4	1020	boro suffer morrison injury blow middlesbrough...

In [44]:
```python
# clean test data
clean_text(test_df, "Text")

# view text in the first row after cleaning all text data
test_df["Text"][0]
```

Out[44]:
```
'qpr keeper day head preston queen park ranger keeper chris day set join preston month loan day displaced arrival simon royce second month loan charlton qpr also signed italian generoso rossi r manager ian holloway said might say risk recalled month simon royce recalled charlton iron fire yes couple others need day ranger contract expires summer meanwhile holloway hoping complete signing middlesbrough defender andy davy either permanently loan saturday match ipswich davy impressed recent loan spell loftus road holloway also chasing bristol city midfielder tom doherty'
```

In [45]:
```python
# use IFIDF to convert words into numerical features
Y = vectorizer.fit_transform(test_df.Text)

# predict test data
yhat_test = predict(best_model.fit_transform(Y))

#create a submission dataframe
test_predictions = pd.DataFrame(columns=['ArticleId', 'Category'])
test_predictions['ArticleId'] = test_df['ArticleId']
test_predictions['yhat'] = yhat_test
n_mapdict = dict(zip(label_order, list(train["Category"].unique())))
test_predictions['Category'] = test_predictions['yhat'].apply(lambda x: n_mapdic

#delete columns unneeded for submission
test_predictions = test_predictions.drop(columns='yhat')

# view some first rows of the result
test_predictions.head()
```

Out[45]:

	ArticleId	Category
0	1018	sport
1	1319	tech
2	1138	sport
3	459	entertainment
4	1020	sport

Step 3: Compare with supervised learning

Since our train data has the categories, we can use supervised models to solve the category of each BBC News article. That is, we look for a classifier that can take a word embedding as an input and predict a text class. To keep things simple, we will use the same preprocessing and word embedding produced by TfidfVectorizer with the same hyperparameters and use RandomForest to train model.

With RandomForest, I use oob_score to evaluate the prediction. The out-of-bag (OOB) error is the average error for each calculated using predictions from the trees that do not contain in their respective bootstrap sample. This allows the RandomForestClassifier to be fit and validated while being trained. And I'll do hyperparameter tuning for Random Forest using GridSearchCV and fit the data.

Random Forest

In [47]:
```
# build RandomForest model
classifier_rf = RandomForestClassifier(random_state=42, n_jobs=-1, max_depth=5,
classifier_rf.fit(X, train.Category)

# checking the oob score
classifier_rf.oob_score_
```

Out[47]:
```
0.8635214827295703
```

Improve Random Forest model

In [48]:
```
# Let’s do hyperparameter tuning for Random Forest using GridSearchCV and fit th
rf = RandomForestClassifier(random_state=42, n_jobs=-1)
params = {
    'max_depth': [2,3,5,10,20],
    'min_samples_leaf': [5,10,20,50,100,200],
    'n_estimators': [10,25,30,50,100,200]
}

# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv = 4,
                           n_jobs=-1, verbose=1, scoring="accuracy")
grid_search.fit(X, train.Category)
```

```
Fitting 4 folds for each of 180 candidates, totalling 720 fits
```

Out[48]:
```
GridSearchCV(cv=4, estimator=RandomForestClassifier(n_jobs=-1, random_state=42),
             n_jobs=-1,
             param_grid={'max_depth': [2, 3, 5, 10, 20],
                         'min_samples_leaf': [5, 10, 20, 50, 100, 200],
                         'n_estimators': [10, 25, 30, 50, 100, 200]},
             scoring='accuracy', verbose=1)
```

In [49]:
```
# get the best score
rf_best_score = grid_search.best_score_
print("\nRandom Forest best score: {:.3f}%".format(rf_best_score*100))

# best model
rf_best = grid_search.best_estimator_
print("\nRandom Forest best model:", rf_best)
```

```
Random Forest best score: 94.103%

Random Forest best model: RandomForestClassifier(max_depth=20, min_samples_leaf=
5, n_estimators=200,
                       n_jobs=-1, random_state=42)
```

Conclusion

From the result above, we can see that unsupervised learning gives a better model with higher accuracy (96.293%) compare with supervised learning Random Forest (94.103%)

Effect of the data size on supervised Random Forest model and unsupervised NMF model

I'm using Learning Curve to determine cross-validated training and test scores for different training set sizes.

A cross-validation generator splits the whole dataset k times in training and test data. Subsets of the training set with varying sizes will be used to train the estimator and a score for each training subset size and the test set will be computed. Afterwards, the scores will be averaged over all k runs for each training subset size.

In [50]:
```
from sklearn.model_selection import learning_curve
```

In [51]:
```
# learning_curve for Random Forest
Xtrain_full = vectorizer.fit_transform(train_df.Text)
ytrain_full = train_df.Category
print('Learning curve for Random Forest model\n')
rf_model = RandomForestClassifier(max_depth=20, min_samples_leaf=5, n_estimators
train_sizes, train_scores, test_scores = learning_curve(rf_model, Xtrain_full, y
```

```
Learning curve for Random Forest model

[learning_curve] Training set sizes: [ 118  385  652  919 1187]
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV] END ...................., score=(train=0.636, test=0.387) total time=   0.2s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s remaining:    0.0s
[CV] END ...................., score=(train=0.974, test=0.906) total time=   0.4s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.7s remaining:    0.0s
[CV] END ...................., score=(train=0.974, test=0.939) total time=   0.5s
[CV] END ...................., score=(train=0.971, test=0.943) total time=   0.5s
[CV] END ...................., score=(train=0.974, test=0.953) total time=   0.7s
[CV] END ...................., score=(train=0.788, test=0.593) total time=   0.2s
[CV] END ...................., score=(train=0.979, test=0.889) total time=   0.3s
[CV] END ...................., score=(train=0.985, test=0.919) total time=   0.5s
[CV] END ...................., score=(train=0.985, test=0.912) total time=   0.5s
[CV] END ...................., score=(train=0.983, test=0.926) total time=   0.6s
[CV] END ...................., score=(train=0.788, test=0.623) total time=   0.2s
[CV] END ...................., score=(train=0.977, test=0.919) total time=   0.3s
[CV] END ...................., score=(train=0.971, test=0.960) total time=   0.4s
[CV] END ...................., score=(train=0.974, test=0.960) total time=   0.6s
[CV] END ...................., score=(train=0.972, test=0.953) total time=   0.6s
[CV] END ...................., score=(train=0.788, test=0.616) total time=   0.2s
[CV] END ...................., score=(train=0.977, test=0.949) total time=   0.3s
[CV] END ...................., score=(train=0.974, test=0.966) total time=   0.4s
[CV] END ...................., score=(train=0.970, test=0.960) total time=   0.5s
[CV] END ...................., score=(train=0.977, test=0.956) total time=   0.7s
[CV] END ...................., score=(train=0.788, test=0.625) total time=   0.2s
[CV] END ...................., score=(train=0.977, test=0.949) total time=   0.3s
```

```
[CV] END ..................., score=(train=0.974, test=0.963) total time=   0.4s
[CV] END ..................., score=(train=0.974, test=0.953) total time=   0.6s
[CV] END ..................., score=(train=0.976, test=0.959) total time=   0.7s
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed:   12.0s finished
```

In [52]:

```
# Manually compute learning curve for NMF model
from tqdm import tqdm
train_scores_nmf = np.zeros((5,len(train_sizes)))
test_scores_nmf = np.zeros((5,len(train_sizes)))

for  i,s in tqdm(enumerate(train_sizes),desc="Learning curve for NMF model\n",to
    for j in range(5):
        try:
            train_df_sub, test_df_sub = train_test_split(train, train_size=s, ra
        except ValueError:
            train_df_sub = train_df

        best_model = NMF(n_components=5, init="nndsvdar", solver = "mu", beta_lo
        X_train = vectorizer.fit_transform(train_df_sub.Text)
        yhat_train_sub = predict(best_model.fit_transform(X_train))
        label_order, train_acc = label_permute_compare(train_df_sub, yhat_train_

        X_test = vectorizer.fit_transform(test_df_sub.Text)
        yhat_test_sub = predict(best_model.fit_transform(X_test))
        label_order, test_acc = label_permute_compare(test_df_sub, yhat_test_sub

        train_scores_nmf[i,j] = train_acc
        test_scores_nmf[i,j] = test_acc
```

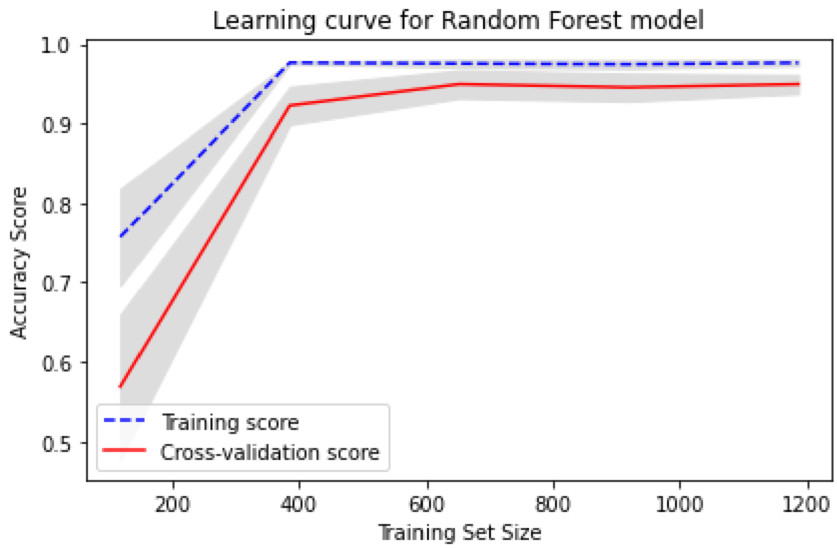
```
Learning curve for NMF model
Learning curve for NMF model | 0/5 [00:00<?, ?it/s]
Learning curve for NMF model00:16<01:04, 16.02s/it]
Learning curve for NMF model00:33<00:51, 17.03s/it]
Learning curve for NMF model00:52<00:35, 17.87s/it]
Learning curve for NMF model01:08<00:17, 17.27s/it]
Learning curve for NMF model01:34<00:00, 20.17s/it]
: 100%|██████████████| 5/5 [01:34<00:00, 18.86s/it]
```

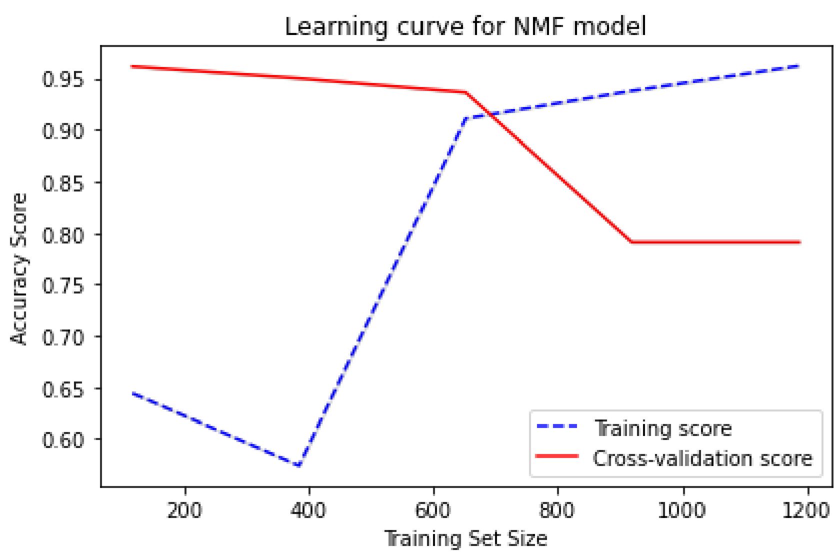
In [53]:

```
def plot_learning_curve(train_sizes, train_scores, test_scores, fig_title):
    train_mean = np.mean(train_scores, axis=1)
    train_std = np.std(train_scores, axis=1)
    test_mean = np.mean(test_scores, axis=1)
    test_std = np.std(test_scores, axis=1)
    #if axes is None:fig, axes = plt.subplots(1, 1, figsize=(10, 5))

    #plt.subplots(1, figsize=(8,8))
    plt.plot(train_sizes, train_mean, '--', color="blue",  label="Training score
    plt.plot(train_sizes, test_mean, color="red", label="Cross-validation score"

    plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std
    plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, co

    plt.title(fig_title)
    plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.legend(lo
    plt.tight_layout()
    plt.show()
```

In [54]:

```
# Plot learning curves
plot_learning_curve(train_sizes, train_scores, test_scores,'Learning curve for R
plot_learning_curve(train_sizes, train_scores_nmf, test_scores_nmf,'Learning cur
```





Conclusion

Looking at two learning curve plots above, we observe that:

- The Random forest model: the larger training set size, the higher accuracy score, especially, when training size is over 400, the accuracy score is improved close to below 100% and stable. So, I think in this case, the more data we have, the higher accuracy score we get.
- The NMF model: is very different from Random Forest model, in overall, when training set size increases, accuracy score increases, especially, when training set size is around 700, the accuracy score is improved a lot, it is over 90%. However, when using less than 600 articles for training, the accuracy score is unstable, it is so slow when training size is less than 400 and then increases close to 90% when training size is around 600. So, increasing the size of the dataset may help increase the accuracy of this NMF model, but the maximum accuracy might not reach 100%.

```
In [ ]:
```