Text Clustering Example

- This example shows text Clustering as an example of unsupervised machine learning task.
- The main steps are:
  - Explore dataset
  - Data Preparation
  - Feature Engineering
  - Model Training
  - Performance Assessment

- Clustering: grouping similar objects together based on their inherent attributes.
- Being unsupervised appraoch there is no need of prelabelled datasets.
- Examples: KMeans, PAM, DBSCAN, Spectral clustering, etc.
- The choice of the algorithm mainly depends on the problem domain and the algorithm property. For example, to use KMeans we should have pre-knowledge of the number of clusters to obtain. However, if we do not know the number of clusters already, then DBSCAN is better.

Problem Definition

- As discussed above, the problem in context is unsupervised learning problem.
- We will use BCC news datasets available from http://mlg.ucd.ie/files/datasets/bbc-fulltext.zip. A total of 2225 documents with five different news categories(i.e. business, entertainment, politics, sport, and tech) are available in the dataset.

In [1]:
```
# Import necessary libraries

import numpy as np
import pandas as pd
from sklearn.cluster import MiniBatchKMeans
from sklearn.cluster import KMeans
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
```

1. Load and explore data

- The dataset contains 5 different categories in 5 different folders.

In [2]:
```
from sklearn.datasets import load_files

# for reproducibility
random_state = 22

DATA_DIR = "./data/bbc/"
data = load_files(DATA_DIR, encoding="utf-8", decode_error="replace", random_state=random_state)
df = pd.DataFrame(list(zip(data['data'], data['target'])), columns=['text', 'label'])
```

It is necessary to do an exploratory data analysis in order to gain some insights from the data.

How is the data like?

In [3]:
```
df.head()
```

Out[3]:

	text	label
0	Jones files Conte lawsuit\n\nMarion Jones has ...	3
1	English clubs make Euro history\n\nAll four of...	3
2	Tarantino 'to make Friday sequel'\n\nDirector ...	1
3	Lesotho textile workers lose jobs\n\nSix forei...	0
4	Celtic make late bid for Bellamy\n\nNewcastle ...	3

how many 'class label' present in the dataset??

In [4]:
```
df['label'].unique()
```

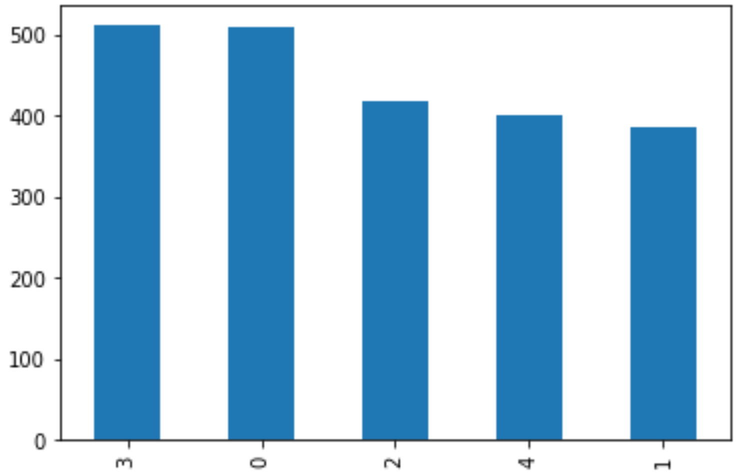
Out[4]:
```
array([3, 1, 0, 4, 2])
```

Is the dataset balanced??

If the dataset is balanced then, the dataset contains an approximately equal portion of each class.

In [5]:
```
df['label'].value_counts().plot(kind='bar')
```

Out[5]: <AxesSubplot:>



2. Feature Engineering

- we will use TFIDF approach.
- TfidfVectorizer will convert all the documents to a matrix of TF-IDF features.
- With Tfidfvectorizer we will calculate the word counts, IDF and TFIDF values in a go.

In [6]:
```
tfidf_vectorizer = TfidfVectorizer(stop_words="english")
tfidf_vectorizer.fit(df.text.values)
features = tfidf_vectorizer.transform(df.text.values)
```

Lets check some values from the first document

In [7]:
```
# get the first vector out (for the first document)
first_vector_tfidfvectorizer=features[0]

# place tf-idf values in a pandas data frame
feature_df = pd.DataFrame(first_vector_tfidfvectorizer.T.todense(), index=tfidf_vectorizer.get_feature_names
feature_df.sort_values(by=["tfidf"],ascending=False).head()
```

Out[7]:

tfidf

	tfidf
conte	0.673159
jones	0.292039
marion	0.213606
doping	0.181978

3. Model Building

- We will check a version of KMeans algorithm, i.e. Mini-batch KMeans (MB KMeans).
- MB KMeans is similar to the standard KMeans. But in the MB KMeans the computationlly expensive step is performed on a random sample only instead of the entire data.
- We will set the number of clusters = 5 because our dataset contains categories.
- But, if we do not have knowledge of the different labels then we may have to using domain knowledge and other ways to get the optimal numbers of clusters.

In [8]:
```
mkmeans = MiniBatchKMeans(n_clusters=5, random_state=random_state)
mkmeans.fit(features)
```

Out[8]:
```
MiniBatchKMeans(n_clusters=5, random_state=22)
```

lets check the predictions useing labels_ attribute of the model.

In [9]:
```
mkmeans.predict(features)
print (mkmeans.labels_)
print ("\n")
print(mkmeans.cluster_centers_)
```

```
[4 2 4 ... 4 4 1]


[[1.34473036e-04 1.09906331e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.68041680e-04 1.05754629e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [2.47895846e-04 2.12690116e-03 0.00000000e+00 ... 0.00000000e+00
```

```
 4.60818743e-04 0.00000000e+00]
[0.00000000e+00 5.00195763e-03 0.00000000e+00 ... 0.00000000e+00
 0.00000000e+00 0.00000000e+00]
[4.67908112e-06 1.15377847e-02 4.45013653e-05 ... 4.09596975e-05
```

Check KMeans

In [10]:
```python
kmeans = KMeans(n_clusters=5, init='k-means++', max_iter=100, n_init=1)
kmeans.fit(features)
kmeans.predict(features)
print (mkmeans.labels_)
print ("\n")
print(mkmeans.cluster_centers_)
```

```
[4 2 4 ... 4 4 1]


[[1.34473036e-04 1.09906331e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.68041680e-04 1.05754629e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [2.47895846e-04 2.12690116e-03 0.00000000e+00 ... 0.00000000e+00
  4.60818743e-04 0.00000000e+00]
 [0.00000000e+00 5.00195763e-03 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [4.67908112e-06 1.15377847e-02 4.45013653e-05 ... 4.09596975e-05
  0.00000000e+00 4.63992050e-04]]
```

In [11]:
```python
# lets order the centroids

order_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]
order_centroids
```

Out[11]:
```
array([[29039,  5711, 27997, ..., 18590, 18591,     0],
       [22845, 12210, 16592, ..., 16826, 16827,     0],
       [17704, 22845, 15294, ..., 15629, 15628, 14562],
       [11464,  9609, 22845, ..., 16998, 16999, 14562],
       [10650,  3844,  3182, ..., 13381, 13382, 14562]])
```

In [12]:
```python
# lets check the features
terms = tfidf_vectorizer.get_feature_names()
terms[23361]
```

Out[12]:
```
'seed'
```

In [13]:
```python
# lets see the centroids into which clusters they belongs
for i in range(5):
    print("\nCluster %d:" % i)
    for ind in order_centroids[i, :10]:
        print('%s' % terms[ind])
```

```
Cluster 0:
yukos
china
virus
oil
microsoft
russian
spyware
gazprom
security
windows

Cluster 1:
said
growth
market
year
economy
sales
bank
company
prices
economic

Cluster 2:
mr
said
labour
people
election
blair
government
party
brown
minister

Cluster 3:
game
```

```
england
said
win
cup
club
match
team
players
play

Cluster 4:
film
best
awards
award
music
band
year
said
films
```

lets do the prediction and check the results

4.Visualization

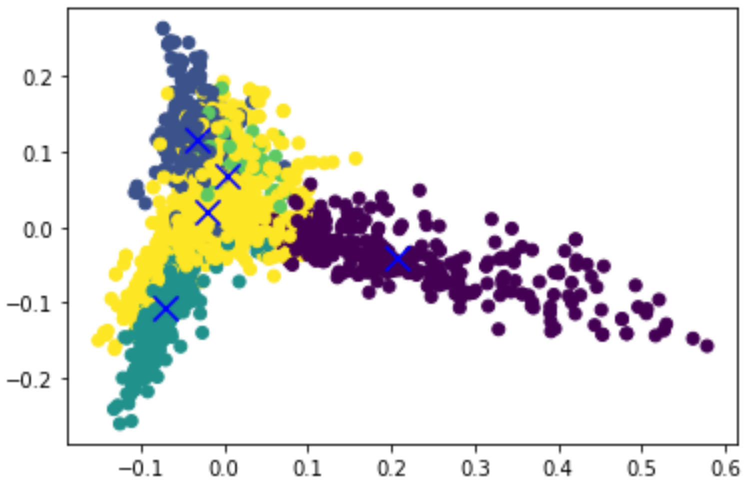
- Lets plot the features in a 2D space.
- The dimension of features got from TfIdfVectorizer is large ($>$ 10,000)so we will do the dimensionality reduction using Principal Component Analysis.
- Here, PCA will transform the high dimensional features into 2 dimensions.

In [14]:
```
def plot_clusters(reduced_features, reduced_cluster_centers, cls):
    plt.scatter(reduced_features[:,0], reduced_features[:,1], c=cls.predict(features))
    plt.scatter(reduced_cluster_centers[:, 0], reduced_cluster_centers[:,1], marker='x', s=150, c='b')

# reduce the features to 2D
pca = PCA(n_components=2, random_state=random_state)
reduced_features = pca.fit_transform(features.toarray())

# reduce the cluster centers to 2D
reduced_cluster_centers_mk = pca.transform(mkmeans.cluster_centers_)
reduced_cluster_centers_k = pca.transform(kmeans.cluster_centers_)
```

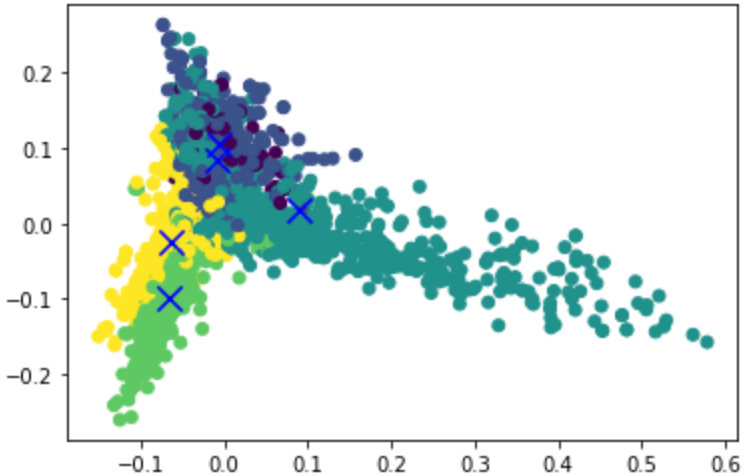
lets visualize using scatter plot.

- In the plot:
    - X = first dimension
    - Y = second dimension
- Different colors represent the cluster members.

In [15]:
```
# MK Means

plot_clusters(reduced_features, reduced_cluster_centers_mk,mkmeans )
```



In [16]:
```
# K Means

plot_clusters(reduced_features, reduced_cluster_centers_k, kmeans)
```



5. Evaluation

- Let us check the predictions.

In [17]:
```
print("Prediction using KMeans")
X = tfidf_vectorizer.transform(["The new social network is popular in cell phones"])
predicted = kmeans.predict(X)
print(predicted)
```

```
Prediction using KMeans
[2]
```

- The prediction label is [2] i.e. cluster 2. It is related with technology and also the examined text is also technology related. This prediction is correct.
- Further, we ahve to test the classifier with other text as well.

In [18]:
```
print("Prediction using Mini Batch KMeans")
X = tfidf_vectorizer.transform(["The new social network is popular in cell phones"])
predicted = mkmeans.predict(X)
print(predicted)
```

```
Prediction using Mini Batch KMeans
[1]
```

Is the prediction accurate??

In [ ]:

```

```

Other formal methods for evaluation:

- Since we have a labelled dataset is easier than the dataset without labelled dataset.
- homogeneity_score: values ranges from 0 and 1 where 1 indicates ideally homogeneous labeling.

In [19]:

```
from sklearn.metrics import homogeneity_score
hs_mk = homogeneity_score(df.label, mkmeans.predict(features))
hs_k = homogeneity_score(df.label, kmeans.predict(features))

print("Homogenity Mini KMeans: %f"%hs_mk)
print("Homogenity KMeans: %f"%hs_k)
```

```
Homogenity Mini KMeans: 0.573055
Homogenity KMeans: 0.619430
```

- In absence of labelled dataset, Cluster evaluation can be done using other metrics like Silhouette Coefficient (SC).
- SC uses mean intra-cluster distance (a) and the mean nearest-cluster distance (b) for each sample.
- Here, b is the distance between a sample and the nearest cluster that the sample is not a part of.
- The SC for a sample is (b - a) / max(a,b).
    - best value = 1
    - worst value = -1
    - near 0 values means overlapping clusters.
    - Negative values means bad clustering.

In [20]:

```
from sklearn.metrics import silhouette_score
ss_mk = silhouette_score(features, labels=mkmeans.predict(features))
ss_k = silhouette_score(features, labels=kmeans.predict(features))

print("silhouette Mini KMeans: %f"%ss_mk)
print("silhouette KMeans: %f"%ss_k)
```

```
silhouette Mini KMeans: 0.009695
silhouette KMeans: 0.009264
```

References:

- https://sanjayasubedi.com.np/nlp/nlp-with-python-document-clustering/
- https://www.kaggle.com/jbencina/clustering-documents-with-tfidf-and-kmeans
- http://kavita-ganesan.com/extracting-keywords-from-text-tfidf/
- https://towardsdatascience.com/applying-machine-learning-to-classify-an-unsupervised-text-document-e7bb6265f52

In [ ]:

```
```