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 (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", ra
df = pd.DataFrame(list(zip(data['data'], data['target'])), columns=['tex
```

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]:

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

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

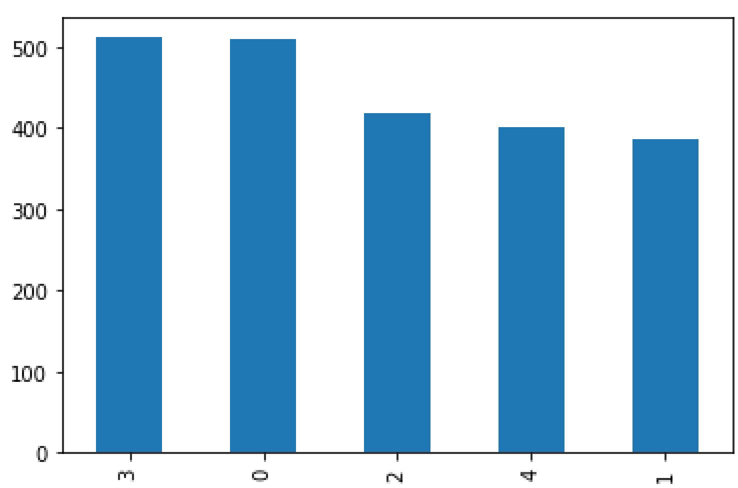
Out[4]:

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]:



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(), ind
feature_df.sort_values(by=["tfidf"],ascending=False).head()
```

Out[7]:

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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]:

lets check the predictions useing labels_ attribute of the model.

In [9]:
```
mkmeans.predict(features)
print mkmeans.labels_
print
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]]
```

Check KMeans

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

```
[1 3 1 ... 1 1 4]

[[0.00000000e+00 1.49656595e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.71467723e-04 1.21722706e-02 7.47173745e-05 ... 1.37541895e-04
  0.00000000e+00 0.00000000e+00]
 [0.00000000e+00 9.52220007e-03 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [1.59264506e-04 2.40800061e-03 0.00000000e+00 ... 0.00000000e+00
  4.79581592e-04 3.92171424e-04]
 [1.45232699e-04 1.02439695e-02 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]]
```

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

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

Out[11]:

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

Out[12]:

In [13]:
```
# 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:
growth
economy
sales
prices
said
economic
year
2004
dollar
bank

Cluster 1:
said
mr
government
new
company
year
film
uk
people
000

Cluster 2:
mr
labour
election
blair
party
said
brown
howard
government
tax

Cluster 3:
best
game
england
film
win
said
year
won
cup
play

Cluster 4:
```

```
mobile
people
said
technology
users
music
digital
software
phone
games
```

lets do the prediction and check the results

4.Visualization

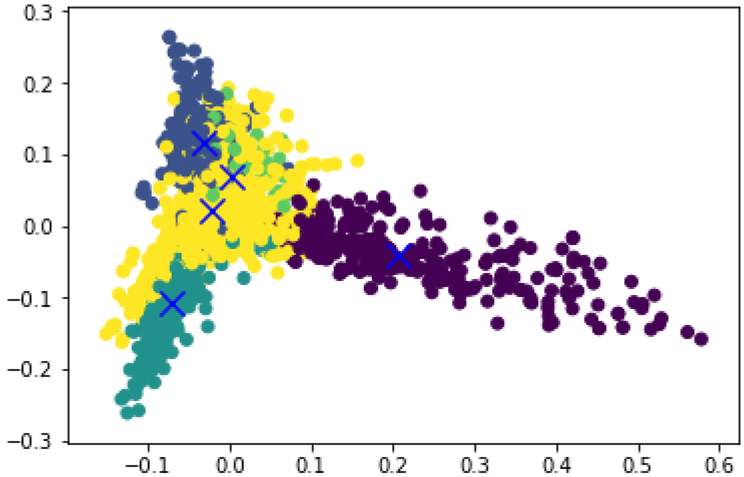
- Lets plot the features in a 2D space.
- The dimension of features got from TfIdfVectorizer is large (> 10,000)so we will do the dimensionality reduction using Principal Component Analysis.
- Here, PCA will transform the high dimensional features into 2 dimensions.

In [14]:
```
def plot_clusters(reduced_features, reduced_cluster_centers, cls):
    plt.scatter(reduced_features[:,0], reduced_features[:,1], c=cls.pre
    plt.scatter(reduced_cluster_centers[:, 0], reduced_cluster_centers[

# 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_)
```

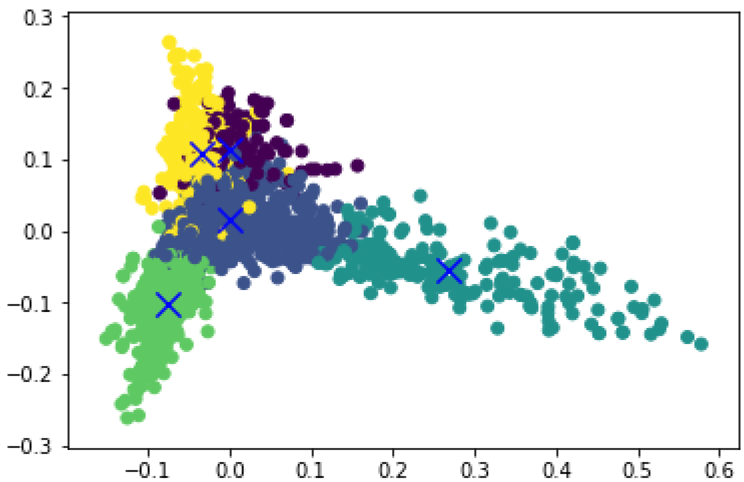
lets visualize using scatter plot.

- 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 co
predicted = kmeans.predict(X)
print(predicted)
```

```
Prediction using KMeans
[4]
```

- 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 co
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: 0.547866
```

- 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: 0.009480
```

References:

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

In [ ]: