Document_Clustering

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0.0.1 Clustering text documents using k-means

As an example we'll be using the 20 newsgroups dataset consists of 18000+ newsgroup posts on 20 topics. You can learn more about the dataset at http://qwone.com/~jason/20Newsgroups/

```
In [14]: from sklearn.datasets import fetch_20newsgroups
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.preprocessing import Normalizer
         from sklearn import metrics
         import matplotlib.pyplot as plt
         from sklearn.cluster import KMeans, MiniBatchKMeans
         import numpy as np
```

0.0.2 Load data

```
In [15]: newsgroups_train = fetch_20newsgroups(subset='train')
         print(list(newsgroups_train.target_names))
```

```
['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc', 'comp.sys.ibm.pc.hardware', 'comp.s
```

To keep it simple, let's filter only 3 topics. Assume that we do not know the topics, let's run clustering algorithm and examine the keywords of each clusters

```
In [16]: categories = ['alt.atheism', 'comp.graphics', 'rec.motorcycles']

         dataset = fetch_20newsgroups(subset='all', categories=categories, shuffle=True, randon

         print("%d documents" % len(dataset.data))
         print("%d categories" % len(dataset.target_names))

         labels = dataset.target

         print("Extracting features from the dataset using a sparse vectorizer")
         vectorizer = TfidfVectorizer(stop_words='english')
         X = vectorizer.fit_transform(dataset.data)

         print("n_samples: %d, n_features: %d" % X.shape)
```

```
2768 documents
3 categories
Extracting features from the dataset using a sparse vectorizer
n_samples: 2768, n_features: 35311
```

0.0.3 LSA via SVD

Latent Semantic Analysis (LSA) is a mathematical method that tries to bring out latent relationships within a collection of documents. Rather than looking at each document isolated from the others it looks at all the documents as a whole and the terms within them to identify relationships. Let's perform LSA by running SVD on the data to reduce the dimensionality.

SVD of matrix A = U * * VT

- r = rank of matrix X
- U = column orthonormal m * r matrix
- = diagonal r * r matrix with singular value sorted in descending order
- V = column orthonormal r * n matrix

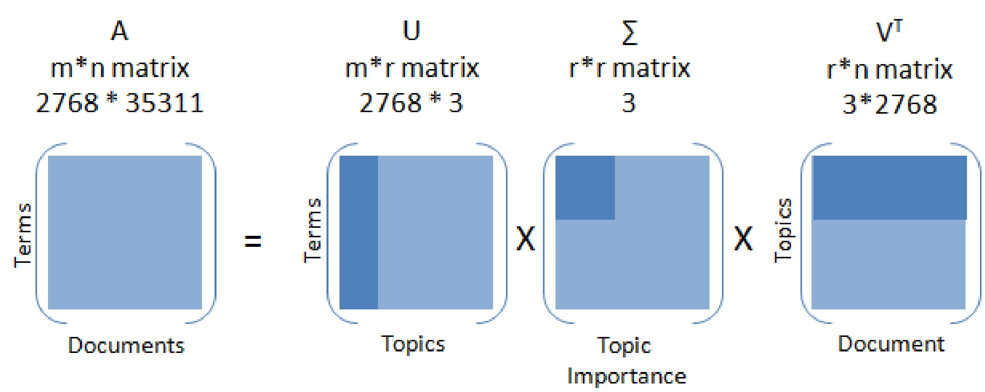
In our case we have 3 topics, 2768 documents and 35311 word vocabulary.

- Original matrix = 2768*35311 ~ 10^8
- SVD = *32768 + 3 +* 335311 ~ 10^5.3

Resulted SVD is taking approximately 460 times less space than original matrix.

```
In [17]: from IPython.display import Image
         Image(filename='../Chapter 5 Figures/SVD.png', width=500)
```

Out[17]:




```
In [18]: from sklearn.decomposition import TruncatedSVD

         # Lets reduce the dimensionality to 2000
```

```
svd = TruncatedSVD(2000)
lsa = make_pipeline(svd, Normalizer(copy=False))

X = lsa.fit_transform(X)

explained_variance = svd.explained_variance_ratio_.sum()
print("Explained variance of the SVD step: {}%".format(int(explained_variance * 100))
```

```
Explained variance of the SVD step: 95%
```

0.0.4 k-means clustering

```
In [13]: from __future__ import print_function

         km = KMeans(n_clusters=3, init='k-means++', max_iter=100, n_init=1)

         # Scikit learn provides MiniBatchKMeans to run k-means in batch mode suitable for a v
         # km = MiniBatchKMeans(n_clusters=5, init='k-means++', n_init=1, init_size=1000, batc

         print("Clustering sparse data with %s" % km)
         km.fit(X)

         print("Top terms per cluster:")
         original_space_centroids = svd.inverse_transform(km.cluster_centers_)
         order_centroids = original_space_centroids.argsort()[:, ::-1]

         terms = vectorizer.get_feature_names()
         for i in range(3):
             print("Cluster %d:" % i, end='')
             for ind in order_centroids[i, :10]:
                 print(' %s' % terms[ind], end='')
             print()
```

```
Clustering sparse data with KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=1(
    n_clusters=3, n_init=1, n_jobs=1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
Top terms per cluster:
Cluster 0: edu graphics university god subject lines organization com posting uk
Cluster 1: com bike edu dod ca writes article sun like organization
Cluster 2: keith sgi livesey caltech com solntze wpd jon edu sandvik
```

0.0.5 Hierarchical clustering

```
In [66]: from sklearn.metrics.pairwise import cosine_similarity
         dist = 1 - cosine_similarity(X)
```

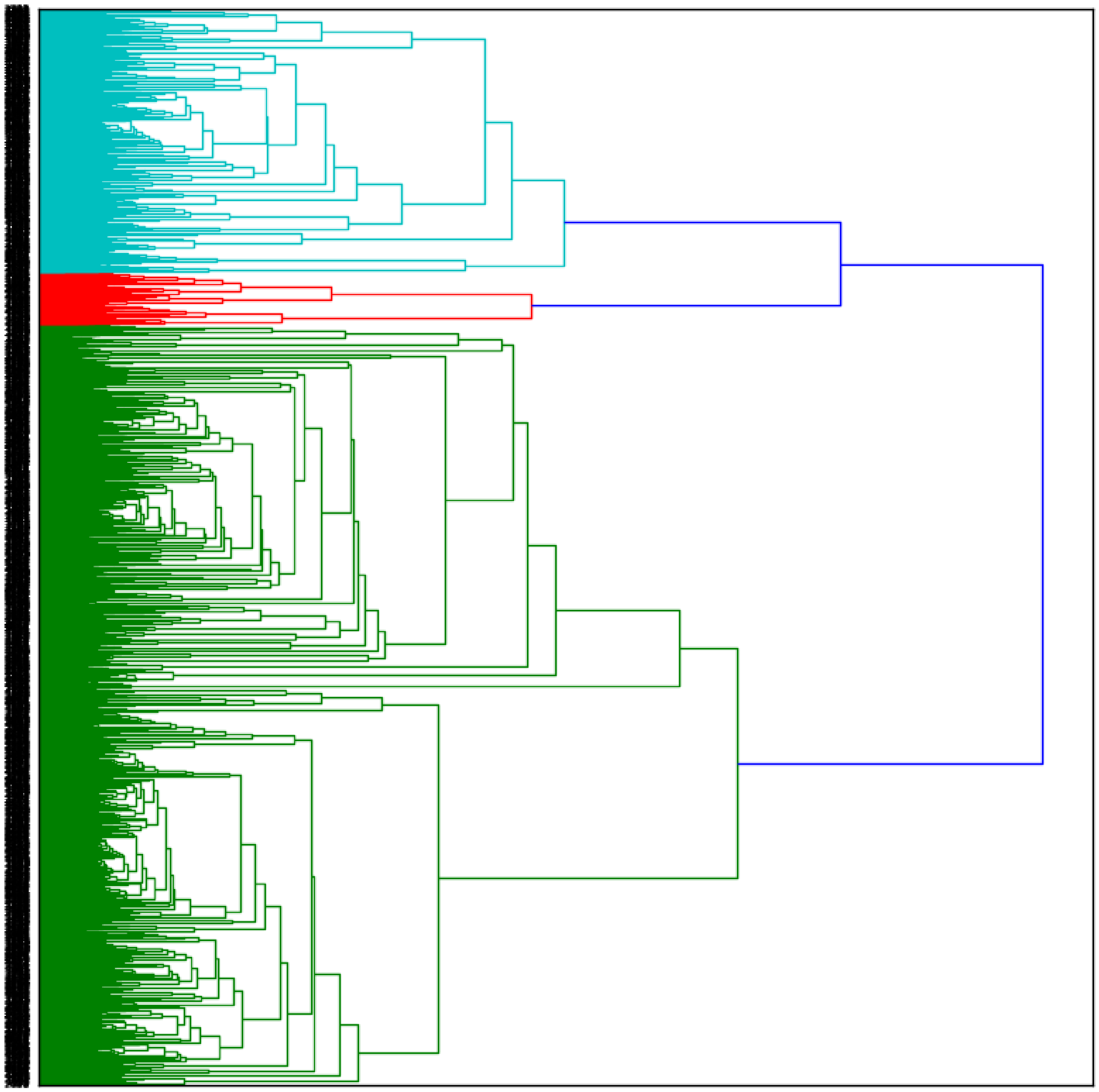
```
In [67]: from scipy.cluster.hierarchy import ward, dendrogram

         linkage_matrix = ward(dist) #define the linkage_matrix using ward clustering pre-comp

         fig, ax = plt.subplots(figsize=(8, 8)) # set size
         ax = dendrogram(linkage_matrix, orientation="right")

         plt.tick_params(axis= 'x', which='both', bottom='off', top='off', labelbottom='off')

         plt.tight_layout() #show plot with tight layout
         plt.show()
```



Reference: Mastering machine learning using python in six-steps book