# clustering_classing

July 2, 2018

### 0.0.1 Clustering and Classification

Code to cluster and classify code for "Natural Language Processing and Computational Linguistics". Lets use two different corpuses to play around with the data.

### 0.0.2 Imports

```
In [1]: # data imports
        from sklearn.datasets import fetch_20newsgroups
        from sklearn.decomposition import TruncatedSVD
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature_extraction.text import HashingVectorizer
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import CountVectorizer

        # clustering imports
        from sklearn.pipeline import make_pipeline
        from sklearn.preprocessing import Normalizer
        from sklearn import metrics
        from sklearn.pipeline import Pipeline
        from sklearn.cluster import KMeans, MiniBatchKMeans

        # classification imports
        from sklearn.feature_selection import SelectFromModel
        from sklearn.feature_selection import SelectKBest, chi2
        from sklearn.linear_model import RidgeClassifier
        from sklearn.svm import LinearSVC
        from sklearn.linear_model import SGDClassifier
        from sklearn.linear_model import Perceptron
        from sklearn.linear_model import PassiveAggressiveClassifier
        from sklearn.naive_bayes import BernoulliNB, MultinomialNB
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.neighbors import NearestCentroid
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.utils.extmath import density
        from sklearn import metrics
```

```
In [2]: # general imports
        import logging
        import sys
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline

        # warnings imports
        import warnings
        warnings.filterwarnings("ignore", category=DeprecationWarning)
```

### 0.0.3 20 NG dataset

In [3]:
```
categories = [
    'alt.atheism',
    'talk.religion.misc',
    'comp.graphics',
    'sci.space',
]
```

In [4]:
```
data_train = fetch_20newsgroups(subset='train', categories=categories,
                                shuffle=True, random_state=42)
```

In [5]:
```
labels = data_train.target
true_k = np.unique(labels).shape[0]
```

In [6]:
```
print("%d documents" % len(data_train.data))
print("%d categories" % len(data_train.target_names))
```

```
2034 documents
4 categories
```

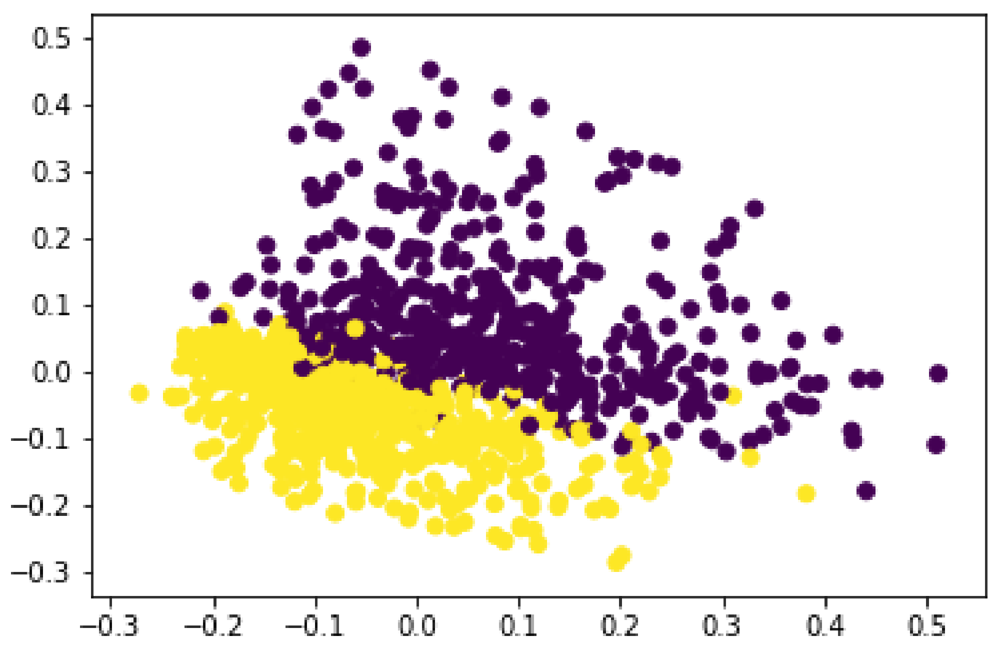
### 0.0.4 Visualising Dataset

In [7]:
```
from sklearn.decomposition import PCA


newsgroups_train = fetch_20newsgroups(subset='train',
                                      categories=['alt.atheism', 'sci.space'])
pipeline = Pipeline([
    ('vect', CountVectorizer()),
    ('tfidf', TfidfTransformer()),
])
X = pipeline.fit_transform(newsgroups_train.data).todense()

pca = PCA(n_components=2).fit(X)
data2D = pca.transform(X)
plt.scatter(data2D[:,0], data2D[:,1], c=newsgroups_train.target)
```

Out[7]: <matplotlib.collections.PathCollection at 0x111c3b050>



### 0.0.5 Vectorizing

```
In [8]: vectorizer = TfidfVectorizer(max_df=0.5, min_df=2, stop_words='english', use_idf=True)
```

```
In [9]: X_train = vectorizer.fit_transform(data_train.data)
```

```
In [10]: print("n_samples: %d, n_features: %d" % X_train.shape)
```

```
n_samples: 2034, n_features: 17259
```

### 0.0.6 Dimensionality Reduction

```
In [11]: n_components = 5
```

```
In [12]: # Vectorizer results are normalized, which makes KMeans behave as
             # spherical k-means for better results. Since LSA/SVD results are
             # not normalized, we have to redo the normalization.
         svd = TruncatedSVD(n_components)
         normalizer = Normalizer(copy=False)
         lsa = make_pipeline(svd, normalizer)

         X_train = lsa.fit_transform(X_train)
```

### 0.0.7 Clustering

We'll start with clustering, and experiment with both k-means and heirarchial clustering.

#### K-means

```
In [13]: minibatch = True
```

```
In [14]: if minibatch:
             km = MiniBatchKMeans(n_clusters=true_k, init='k-means++', n_init=1, init_size=1000,
         batch_size=1000)
         else:
             km = KMeans(n_clusters=true_k, init='k-means++', max_iter=100, n_init=1)

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

```
Clustering sparse data with MiniBatchKMeans(batch_size=1000, compute_labels=True,
init='k-means++',
        init_size=1000, max_iter=100, max_no_improvement=10, n_clusters=4,
        n_init=1, random_state=None, reassignment_ratio=0.01, tol=0.0,
        verbose=0)
```

```
Out[14]: MiniBatchKMeans(batch_size=1000, compute_labels=True, init='k-means++',
                 init_size=1000, max_iter=100, max_no_improvement=10, n_clusters=4,
                 n_init=1, random_state=None, reassignment_ratio=0.01, tol=0.0,
                 verbose=0)
```

```
In [15]: print("Homogeneity: %0.3f" % metrics.homogeneity_score(labels, km.labels_))
         print("Completeness: %0.3f" % metrics.completeness_score(labels, km.labels_))
         print("V-measure: %0.3f" % metrics.v_measure_score(labels, km.labels_))
         print("Adjusted Rand-Index: %.3f"
               % metrics.adjusted_rand_score(labels, km.labels_))
         print("Silhouette Coefficient: %0.3f"
               % metrics.silhouette_score(X_train, km.labels_, sample_size=1000))
```

```
Homogeneity: 0.616
Completeness: 0.653
V-measure: 0.634
Adjusted Rand-Index: 0.633
Silhouette Coefficient: 0.472
```

```
In [16]: original_space_centroids = svd.inverse_transform(km.cluster_centers_)
         order_centroids = original_space_centroids.argsort()[:, ::-1]
         terms = vectorizer.get_feature_names()
```

```
In [17]: for i in range(true_k):
             print("Cluster %d:" % i)
             for ind in order_centroids[i, :10]:
                 print(' %s' % terms[ind])
```

```
Cluster 0:
 keith
 caltech
 sgi
 livesey
 morality
 wpd
 solntze
 com
 objective
 jon
Cluster 1:
 space
 nasa
 henry
 toronto
 alaska
 gov
 com
 access
 moon
 article
Cluster 2:
 god
 people
 jesus
 com
 don
 say
 bible
 believe
 think
 just
Cluster 3:
 graphics
 space
 com
```

```
nasa
university
image
posting
files
host
thanks
```

### 0.0.8 Heirarchial Clustering

To do heirarchial clustering we need pairwise distances.

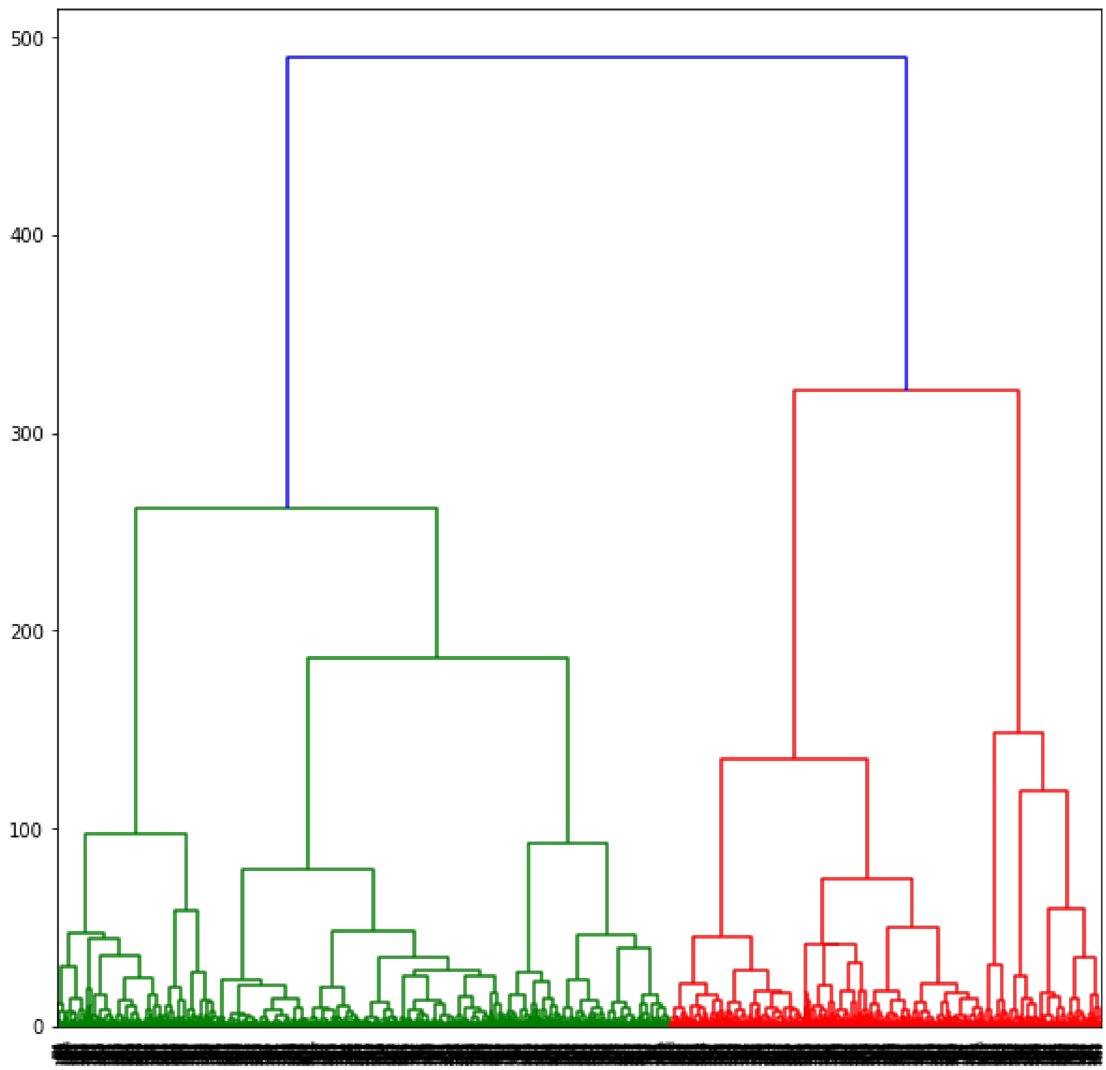
```
In [18]: from sklearn.metrics.pairwise import cosine_similarity
         dist = 1 - cosine_similarity(X_train)
```

```
In [19]: from scipy.cluster.hierarchy import ward, dendrogram
```

```
In [20]: # titles = ?
```

```
In [21]: linkage_matrix = ward(dist) #define the linkage_matrix using ward clustering pre-
         computed distances
```

```
In [22]: fig, ax = plt.subplots(figsize=(10, 10)) # set size
         ax = dendrogram(linkage_matrix)
```




### 0.0.9 Classification

#### Data

In [23]:
```
# order of labels in `target_names` can be different from `categories`
data_test = fetch_20newsgroups(subset='test', categories=categories,
                               shuffle=True, random_state=42)

target_names = data_train.target_names

# split a training set and a test set
y_train, y_test = data_train.target, data_test.target

print("Extracting features from the test data using the same vectorizer")
X_test = vectorizer.transform(data_test.data)
X_test = lsa.fit_transform(X_test)
```

```
Extracting features from the test data using the same vectorizer
```

### 0.0.10 Classification

```
In [24]: from sklearn.naive_bayes import GaussianNB
```

```
In [25]: gnb = GaussianNB()
         y_pred_NB = gnb.fit(X_train, y_train).predict(X_test)
```

```
In [26]: from sklearn.svm import SVC
```

```
In [27]: svm = SVC()
         y_pred_SVM = svm.fit(X_train, y_train).predict(X_test)
```

### 0.0.11 Classification Report

The precision is the percentage of the test samples that were classified to the category and actually belonged to the category.

The recall is the percentage of all the test samples that originally belonged to the category and in the evaluation process were correctly classified to the category

```
In [28]: from sklearn.metrics import classification_report
```

```
In [29]: print(classification_report(y_test, y_pred_NB))
```

```
             precision    recall  f1-score   support

          0       0.00      0.00      0.00       319
          1       0.00      0.00      0.00       389
          2       0.00      0.00      0.00       394
          3       0.10      0.27      0.14       251

avg / total       0.02      0.05      0.03      1353
```

```
In [30]: np.mean(y_pred_SVM == y_test)
```

```
Out[30]: 0.038433111603843315
```

```
In [31]: y_test
```

```
Out[31]: array([2, 1, 1, ..., 3, 1, 1])
```

```
In [32]: y_pred_NB
```

```
Out[32]: array([0, 3, 3, ..., 3, 3, 3])
```