Introduction-SciKit-Learn-Clustering

December 4, 2019

1 Introduction to Sci-Kit Learn and Clustering

In this tutorial we will introduce the Sci-Kit Learn library:https://scikit-learn.org/stable/

This is a very important library with a huge toolkit for data processing, unsupervised and supervised learning. It is one of the core tools for data science.

We will see some of the capabilities of this toolkit and focus on clustering.

[1]:
```
import numpy as np
import scipy as sp
import scipy.sparse as sp_sparse
import scipy.spatial.distance as sp_dist

import matplotlib.pyplot as plt

import sklearn as sk
import sklearn.datasets as sk_data
import sklearn.metrics as metrics
from sklearn import preprocessing
import sklearn.cluster as sk_cluster
import sklearn.feature_extraction.text as sk_text


import scipy.cluster.hierarchy as hr

import time
import seaborn as sns

%matplotlib inline
```

1.1 Computing distances

For the computation of distances there are libraries in Scipy

http://docs.scipy.org/doc/scipy-0.15.1/reference/spatial.distance.html#module-scipy.spatial.distance

but also in SciKit metrics library:

http://scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.pairwise_distances.html

Compute distance between vectors

[2]:
```
import scipy.spatial.distance as sp_dist

x = np.random.randint(2, size = 5)
y = np.random.randint(2, size = 5)
print (x)
print (y)
print (sp_dist.cosine(x,y))
print (sp_dist.euclidean(x,y))
print (sp_dist.jaccard(x,y))
print (sp_dist.hamming(x,y))
```

```
[1 0 1 1 1]
[1 0 0 1 0]
0.29289321881345254
1.4142135623730951
0.5
0.4
```

Compute pairwise distances in a table

[3]:
```
A = np.random.randint(2, size = (5,3))

# computes the matrix of all pairwise distances of rows
# returns a vector with N(N-1)/2 entries (N number of rows)
D = sp_dist.pdist(A, 'jaccard')
print (A)
print('\n all row distances')
print (D)
# When computing jaccard similarity of 0/1 matrices,
# 1 means that the element corresponding to the column is in the set,
# 0 that the element is not in the set
```

```
[[0 1 1]
 [1 0 1]
 [0 1 1]
 [1 1 0]
 [0 1 0]]

 all row distances
[0.66666667 0.         0.66666667 0.5        0.66666667 0.66666667
 1.         0.66666667 0.5        0.5       ]
```

Compute distances using sklearn

[4]:
```
import sklearn.metrics as metrics

#computes the matrix of all pairwise distances of rows
# returns a NxN matrix (N number of rows)
D2 = metrics.pairwise.pairwise_distances(A,metric = 'jaccard')
```

```
print('\n the matrix of row distances')
print(D2)
```

```
 the matrix of row distances
[[0.         0.66666667 0.         0.66666667 0.5       ]
 [0.66666667 0.         0.66666667 0.66666667 1.        ]
 [0.         0.66666667 0.         0.66666667 0.5       ]
 [0.66666667 0.66666667 0.66666667 0.         0.5       ]
 [0.5        1.         0.5        0.5        0.        ]]

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\pairwise.py:1575:
DataConversionWarning: Data was converted to boolean for metric jaccard
  warnings.warn(msg, DataConversionWarning)
```

Compute distances between the rows of two tables

[5]:
```
B = np.random.randint(2, size = (3,3))
print (B)

#computes the matrix of all pairwise distances of rows of A with rows of B
# returns an NxM matrix (N rows of A, M rows of B)
D3 = metrics.pairwise.pairwise_distances(A,B,metric = 'jaccard')
print('\n the matrix of distances between the rows of A and B')
print(D3)
```

```
[[1 1 1]
 [0 1 1]
 [0 0 0]]

 the matrix of distances between the rows of A and B
[[0.33333333 0.         1.        ]
 [0.33333333 0.66666667 1.        ]
 [0.33333333 0.         1.        ]
 [0.33333333 0.66666667 1.        ]
 [0.66666667 0.5        1.        ]]

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\pairwise.py:1575:
DataConversionWarning: Data was converted to boolean for metric jaccard
  warnings.warn(msg, DataConversionWarning)
```

We can apply everything to sparce matrices

[5]:
```
d = np.array([[0, 0, 12],
              [0, 1, 1],
              [0, 5, 34],
              [1, 3, 12],
              [1, 2, 6],
              [2, 0, 23],
```

```
              [3, 4, 14],
              ])
s = sp_sparse.csr_matrix((d[:,2],(d[:,0],d[:,1])), shape=(4,6))
D4 = metrics.pairwise.pairwise_distances(s,metric = 'euclidean')
print(s.toarray())
print(D4)
```

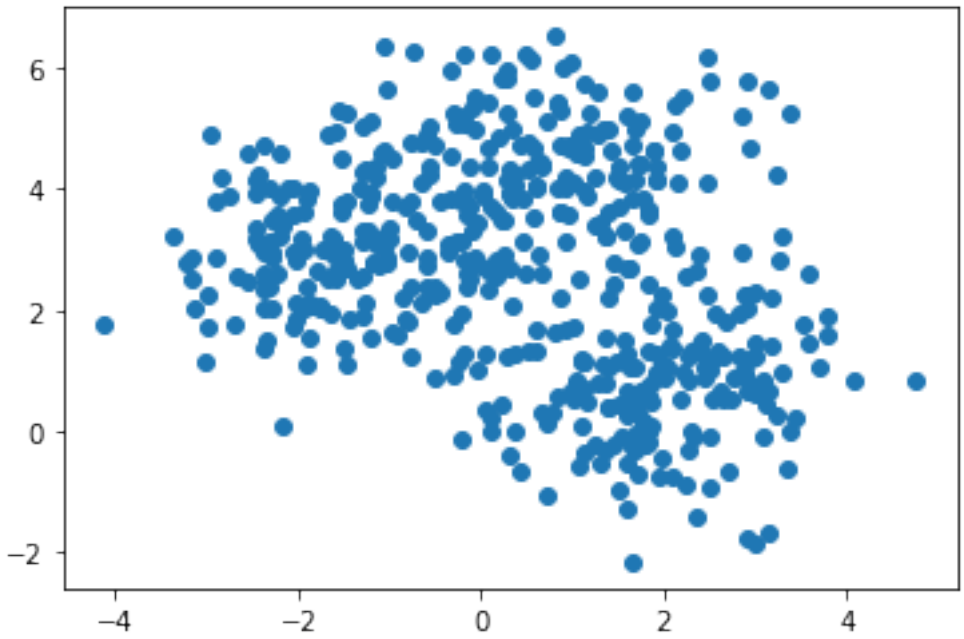
```
[[12  1  0  0  0 34]
 [ 0  0  6 12  0  0]
 [23  0  0  0  0  0]
 [ 0  0  0  0 14  0]]
[[ 0.         38.48376281 35.74912586 38.69108424]
 [38.48376281  0.         26.62705391 19.39071943]
 [35.74912586 26.62705391  0.         26.92582404]
 [38.69108424 19.39071943 26.92582404  0.        ]]
```

1.2 Clustering

You can read more about clustering in SciKit here:
http://scikit-learn.org/stable/modules/clustering.html
Generate data from Gaussian distributions.
More on data generation here: http://scikit-learn.org/stable/modules/generated/sklearn.datasets.make_blo

[6]:
```
centers = [[1,1], [-1, -1], [1, -1]]
X, true_labels = sk_data.make_blobs(n_samples=500, centers=3, n_features=2,
                                    center_box=(-10.0, 10.0),random_state=0)
plt.scatter(X[:,0], X[:,1])
```

[6]: `<matplotlib.collections.PathCollection at 0x2b6dacddfd0>`

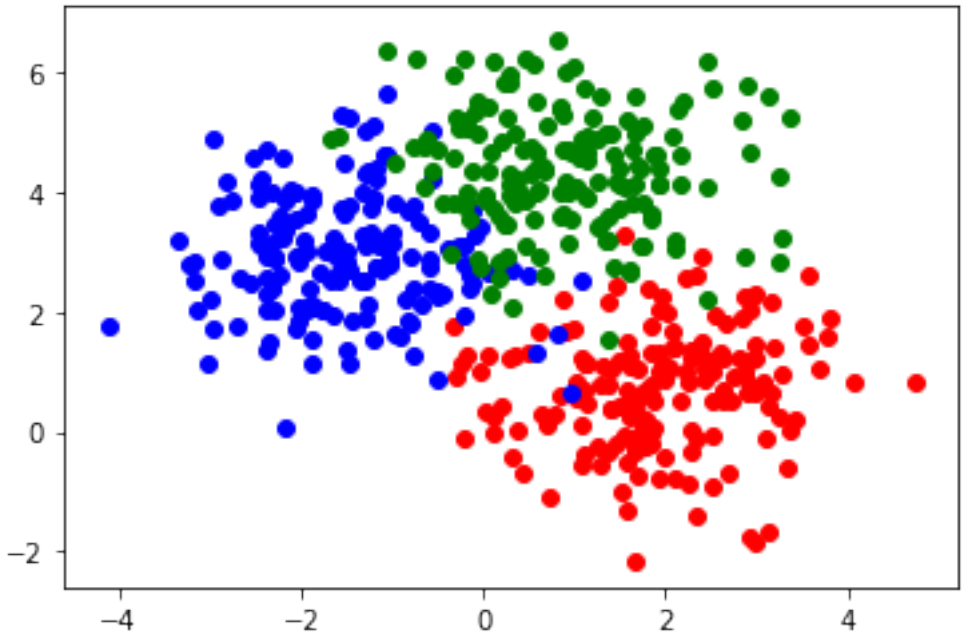


[7]:
```
print(type(X))
print(true_labels)
print(len(true_labels[true_labels==0]),len(true_labels[true_labels==1]),len(true_labels[true_l
```

```
<class 'numpy.ndarray'>
[0 2 2 0 0 0 0 2 2 0 2 2 2 2 0 0 1 0 2 0 1 1 1 2 0 2 1 2 0 2 2 0 0 0 1 1 1
 1 1 1 2 0 0 1 1 0 1 0 2 2 0 0 0 0 2 2 1 1 0 2 1 2 1 1 1 2 0 1 2 0 2 0 0 2
 1 2 1 1 1 0 0 0 2 0 2 1 2 2 2 2 0 0 1 0 2 1 2 2 2 0 1 2 2 0 0 1 0 1 0 1 0
 0 1 2 2 1 2 1 1 2 2 0 2 2 2 0 2 0 2 0 1 0 2 1 0 1 2 2 1 0 0 2 2 1 0 0 0 1
 1 0 1 0 0 0 1 0 2 1 2 0 1 1 2 2 2 1 0 1 0 1 2 2 1 0 0 2 2 1 1 1 1 1 2 2 1
 1 0 1 0 2 2 0 1 1 0 2 1 0 2 1 2 1 0 0 2 1 1 1 2 2 0 1 1 2 2 0 2 0 2 2 1 2
 1 1 0 0 0 1 2 0 0 2 2 1 2 2 0 1 0 0 0 1 1 1 0 2 2 2 2 2 1 2 2 0 2 2 0 1 2
 1 1 0 0 1 1 0 2 1 2 1 1 2 1 0 0 1 0 1 1 1 1 2 1 0 0 0 0 2 2 1 1 2 2 0 0 1
 2 0 2 1 0 1 2 1 0 2 0 1 0 2 1 2 2 0 0 0 1 2 2 0 0 1 2 1 0 0 1 1 0 2 1 0 1
 2 1 1 0 2 0 2 1 2 1 0 0 0 1 0 0 2 1 0 2 2 2 0 1 1 1 2 0 1 2 0 0 0 2 0 2 0
 2 2 0 2 2 2 2 1 1 2 1 2 2 2 2 0 0 0 1 2 0 1 0 1 0 1 2 2 0 2 1 0 1 2 2 0 1
 2 1 2 0 0 0 1 2 0 0 1 2 2 0 2 1 0 2 0 1 0 2 0 0 1 0 0 0 0 1 0 1 2 1 1 0 2
 1 2 1 2 1 0 2 1 1 1 1 1 0 2 1 2 0 0 1 2 2 0 2 1 0 0 1 1 2 1 2 1 1 1 1 2 0
 1 1 0 1 2 2 0 1 1 2 0 2 0 0 1 1 1 0 1]
167 167 166
```

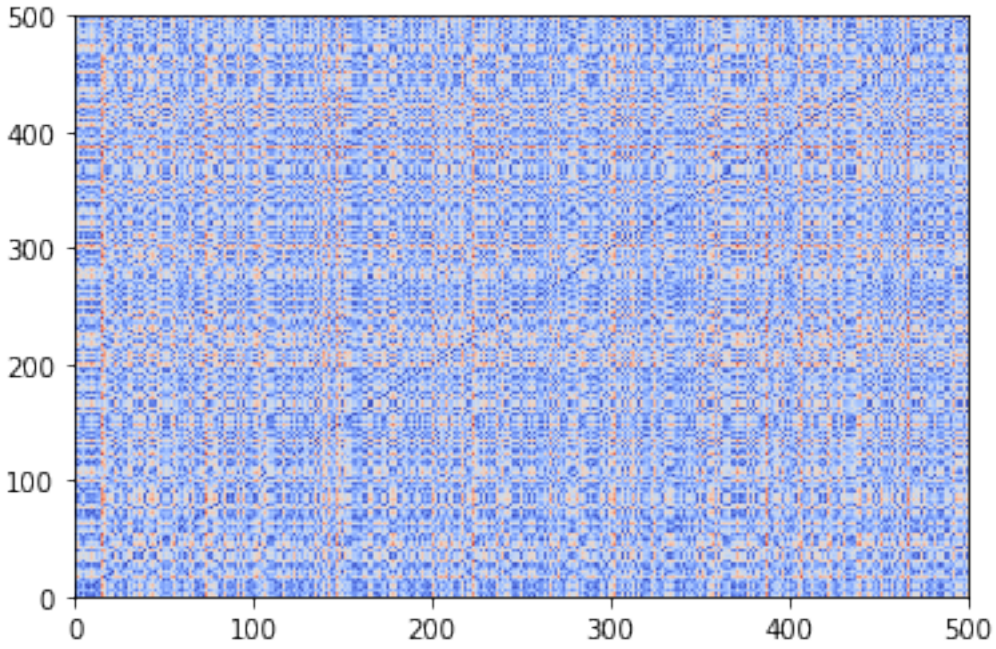
[8]:
```
plt.scatter(X[true_labels==1,0], X[true_labels==1,1],c = 'r')
plt.scatter(X[true_labels==2,0], X[true_labels==2,1],c = 'b')
plt.scatter(X[true_labels==0,0], X[true_labels==0,1],c = 'g')
```

[8]: <matplotlib.collections.PathCollection at 0x2b6dad9a390>



[9]:
```
euclidean_dists = metrics.euclidean_distances(X)
plt.pcolor(euclidean_dists,cmap=plt.cm.coolwarm)
```

[9]:
```
<matplotlib.collections.PolyCollection at 0x2b6dadf51d0>
```



1.3 Clustering Algorithms

scikit-learn has a huge set of tools for unsupervised learning generally, and clustering specifically. These are in sklearn.cluster. http://scikit-learn.org/stable/modules/clustering.html

There are 3 functions in all the clustering classes,
fit(),
predict(),
fit_predict().
fit() builds the model from the training data (e.g. for kmeans, it finds the centroids),
predict() assigns labels to the data after building the model, and
fit_predict() does both at the same data (e.g in kmeans, it finds the centroids and assigns the labels to the dataset).

1.3.1 K-means clustering

More on the k-means clustering here: http://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans

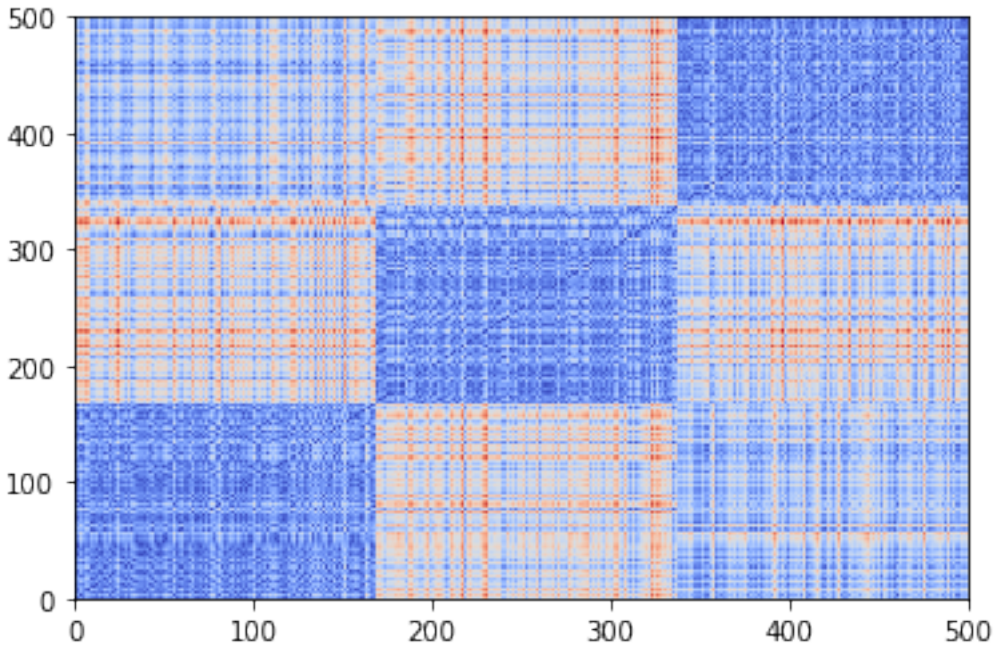
[10]:
```
import sklearn.cluster as sk_cluster

kmeans = sk_cluster.KMeans(init='k-means++', n_clusters=3, n_init=10)
```

```
kmeans.fit_predict(X)
centroids = kmeans.cluster_centers_
kmeans_labels = kmeans.labels_
error = kmeans.inertia_

print ("The total error of the clustering is: ", error)
print ('\nCluster labels')
print(kmeans_labels)
print ('\n Cluster Centroids')
print (centroids)
```

```
The total error of the clustering is:  881.748277486619

Cluster labels
[2 0 0 2 0 2 0 0 0 2 0 0 0 0 2 2 1 2 0 2 2 1 1 0 2 0 1 0 2 0 0 2 2 0 1 1 1
 1 1 1 0 2 2 1 1 2 1 2 0 0 2 2 2 2 0 0 1 1 2 1 1 0 1 1 1 0 1 1 0 2 0 2 2 0
 1 0 1 1 1 2 2 2 0 2 0 1 0 0 0 0 2 2 1 2 0 1 0 2 0 2 1 0 0 2 2 1 2 1 2 1 2
 2 1 0 0 1 0 1 1 0 0 1 2 0 0 2 0 2 0 2 1 2 0 1 2 1 0 0 1 2 2 2 0 1 2 2 2 1
 1 2 1 2 2 2 1 2 0 1 0 2 1 1 0 0 0 1 2 1 2 1 0 0 1 2 2 0 0 1 1 1 1 1 0 0 1
 1 2 1 0 0 0 2 1 1 2 0 1 2 0 1 0 1 2 2 0 1 1 1 0 0 2 1 1 0 0 2 0 2 0 0 1 0
 1 1 2 2 2 1 0 2 2 0 0 1 0 0 2 1 2 2 2 1 1 1 2 0 0 0 0 0 1 0 0 2 0 0 2 1 0
 1 1 2 2 1 1 2 0 1 0 1 1 0 1 2 0 1 2 1 1 1 1 0 1 2 2 2 2 0 0 0 1 0 0 2 2 1
 0 2 0 1 2 1 0 1 2 0 2 1 2 0 1 0 0 2 0 2 1 0 0 2 2 1 2 1 2 2 2 1 2 0 1 1 1
 0 1 1 2 0 0 0 1 0 1 2 2 2 1 2 0 0 1 2 0 0 0 1 1 1 1 0 2 1 0 2 2 2 1 2 0 2
 0 0 2 0 0 0 0 1 1 0 1 2 0 2 0 2 2 0 1 0 0 1 2 1 2 1 0 0 2 2 1 2 1 0 0 2 1
 0 1 0 2 2 0 1 1 2 2 1 0 0 2 0 1 2 0 2 1 2 0 2 2 1 2 2 2 2 1 2 1 0 1 0 2 0
 1 0 1 0 1 2 0 1 1 1 1 1 2 0 1 0 2 2 1 0 0 0 0 1 2 2 1 1 2 1 0 1 1 0 1 2 2
 1 1 2 1 0 0 2 1 1 0 2 0 2 2 1 1 1 2 1]

 Cluster Centroids
[[-1.52371332  2.92068825]
 [ 1.96167358  0.73752985]
 [ 0.87564159  4.45514163]]
```

[11]:
```
idx = np.argsort(kmeans_labels) # returns the indices in sorted order
rX = X[idx,:]
r_euclid = metrics.euclidean_distances(rX)
#r_euclid = euclidean_dists[idx,:][:,idx]
plt.pcolor(r_euclid,cmap=plt.cm.coolwarm)
```

[11]:
```
<matplotlib.collections.PolyCollection at 0x2b6dd434358>
```



Confusion matrix: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.htm

Important: In the produced confusion matrix, the first list defines the rows and the second the columns. The matrix is always square, regarless if the number of classes and clusters are not the same. The extra rows or columns are filled with zeros.

Homogeneity and completeness: http://scikit-learn.org/stable/modules/clustering.html#homogeneity-completeness

Precision: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_score.html#sklearn.

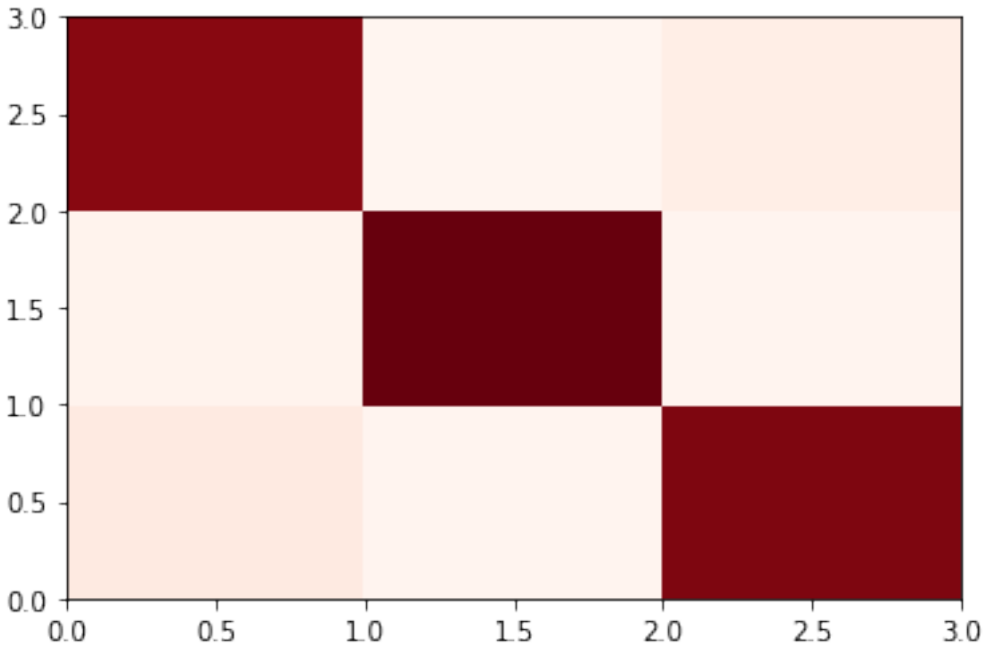
Recall: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.recall_score.html#sklearn.metrics

Silhouette score: http://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html

[12]:
```
C= metrics.confusion_matrix(kmeans_labels,true_labels)
print (C)
plt.pcolor(C,cmap=plt.cm.Reds)
```

```
[[ 12   3 154]
 [  4 162   3]
 [151   2   9]]
```

[12]:
```
<matplotlib.collections.PolyCollection at 0x2b6ea8ec4a8>
```



Compute precision and recall.
These metrics are for classification, so they assume that row i is mapped to column i

[13]:
```
p = metrics.precision_score(true_labels,kmeans_labels, average=None)
print(p)
r = metrics.recall_score(true_labels,kmeans_labels, average = None)
print(r)
```

```
[0.07100592 0.95857988 0.05555556]
[0.07185629 0.97005988 0.05421687]
```

Create a function that maps each cluster to the class that has the most points.
You need to be careful if many clusters map to the same class. It will not work in this case

[14]:
```
def cluster_class_mapping(kmeans_labels,true_labels):
    C= metrics.confusion_matrix(kmeans_labels,true_labels)
    mapping = list(np.argmax(C,axis=1)) #for each row (cluster) find the best␣
 ↪class in the confusion matrix
    mapped_kmeans_labels = [mapping[l] for l in kmeans_labels]
    C2= metrics.confusion_matrix(mapped_kmeans_labels,true_labels)
    return mapped_kmeans_labels,C2

mapped_kmeans_labels,C = cluster_class_mapping(kmeans_labels,true_labels)
print(C)
```

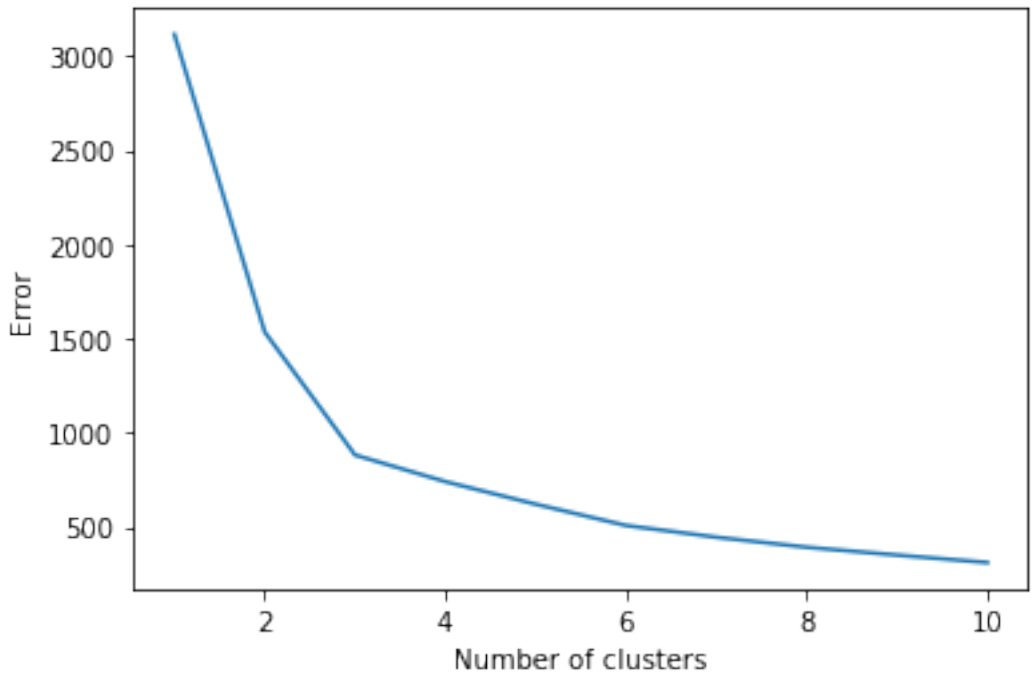
```
[[151   2   9]
 [  4 162   3]
 [ 12   3 154]]
```

[15]:
```
h = metrics.homogeneity_score(true_labels,kmeans_labels)
print(h)
c = metrics.completeness_score(true_labels,kmeans_labels)
print(c)
v = metrics.v_measure_score(true_labels,kmeans_labels)
print(v)
p = metrics.precision_score(true_labels,mapped_kmeans_labels, average=None)
print(p)
r = metrics.recall_score(true_labels,mapped_kmeans_labels, average = None)
print(r)
p = metrics.precision_score(true_labels,mapped_kmeans_labels,␣
 ↪average='weighted')
print(p)
r = metrics.recall_score(true_labels,mapped_kmeans_labels, average = 'weighted')
print(r)
```

```
0.7497037574992788
0.7498354394270632
0.7497695926813515
[0.93209877 0.95857988 0.9112426 ]
[0.90419162 0.97005988 0.92771084]
0.934019212506392
0.934
```

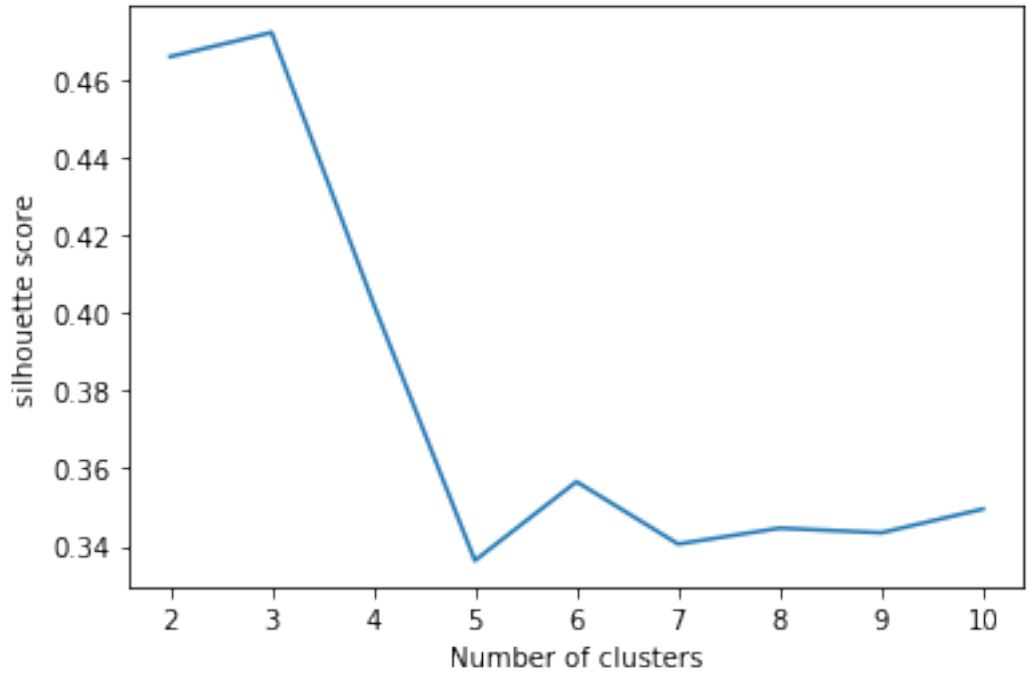
[16]:
```
error = np.zeros(11)
sh_score = np.zeros(11)
for k in range(1,11):
    kmeans = sk_cluster.KMeans(init='k-means++', n_clusters=k, n_init=10)
    kmeans.fit_predict(X)
    error[k] = kmeans.inertia_
    if k>1: sh_score[k]= metrics.silhouette_score(X, kmeans.labels_)

plt.plot(range(1,len(error)),error[1:])
plt.xlabel('Number of clusters')
plt.ylabel('Error')
```

[16]:
```
Text(0, 0.5, 'Error')
```



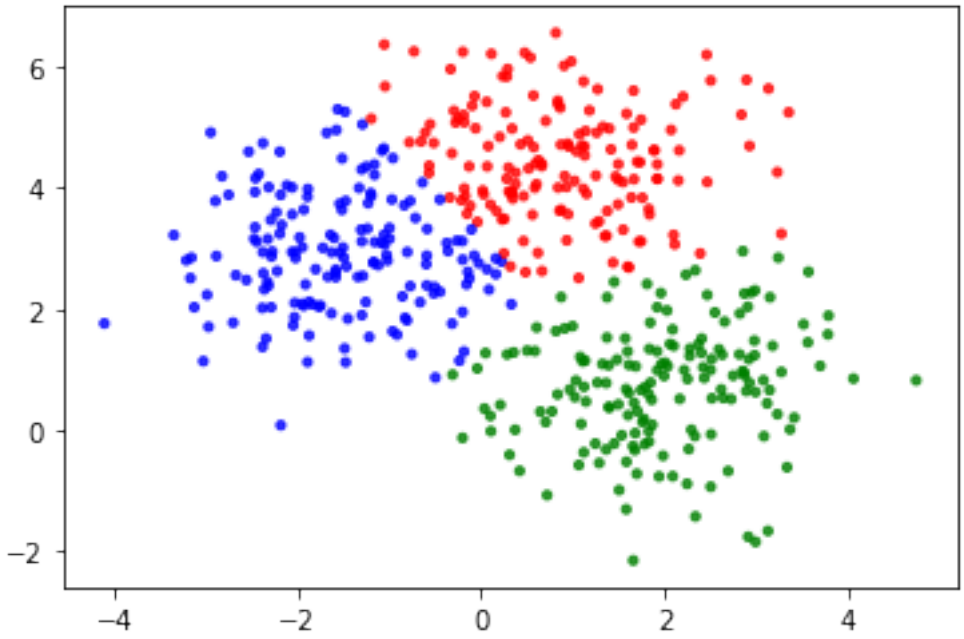
[17]:
```
plt.plot(range(2,len(sh_score)),sh_score[2:])
plt.xlabel('Number of clusters')
plt.ylabel('silhouette score')
```

[17]:
```
Text(0, 0.5, 'silhouette score')
```



[18]:
```
colors = np.array([x for x in 'bgrcmykbgrcmykbgrcmykbgrcmyk'])
colors = np.hstack([colors] * 20)
plt.scatter(X[:, 0], X[:, 1], color=colors[kmeans_labels].tolist(), s=10,␣
↪alpha=0.8)
```

[18]:
```
<matplotlib.collections.PathCollection at 0x2b6eaa1db70>
```

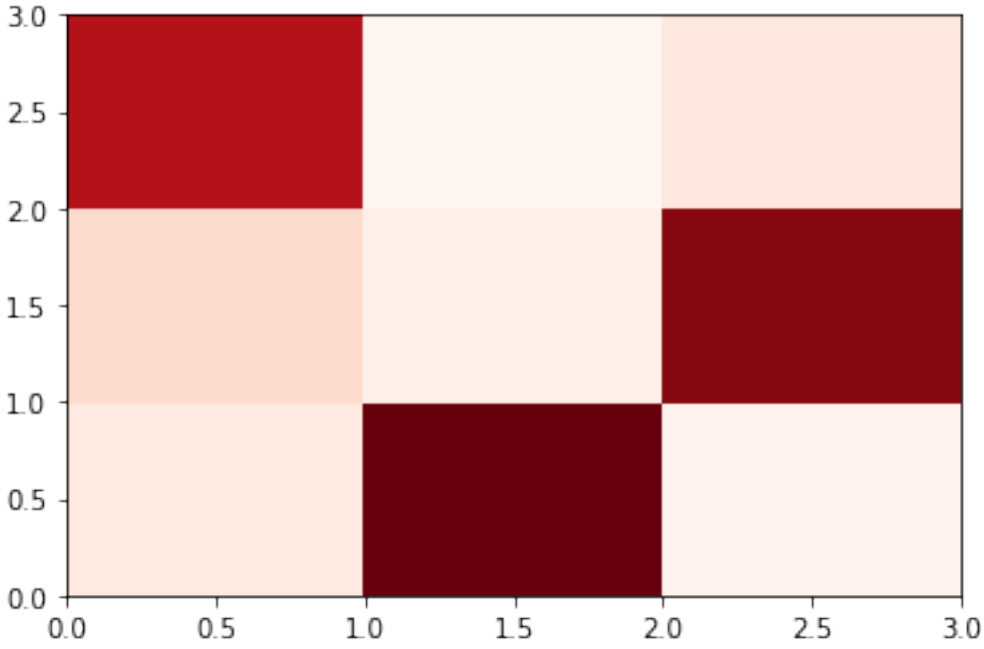


1.3.2 Agglomerative Clustering

More on Agglomerative Clustering here: http://scikit-learn.org/stable/modules/generated/sklearn.cluster.Agg

[19]:
```
agglo = sk_cluster.AgglomerativeClustering(linkage = 'complete', n_clusters = 3)
agglo_labels = agglo.fit_predict(X)

C_agglo= metrics.confusion_matrix(agglo_labels,true_labels)
print (C_agglo)
#plt.pcolor(C_agglo,cmap=plt.cm.coolwarm)
plt.pcolor(C_agglo,cmap=plt.cm.Reds)

mapped_agglo_labels,C_agglo = cluster_class_mapping(agglo_labels,true_labels)
print(C_agglo)
p = metrics.precision_score(true_labels,mapped_agglo_labels, average='weighted')
print(p)
r = metrics.recall_score(true_labels,mapped_agglo_labels, average = 'weighted')
print(r)
```

```
[[ 12 159   3]
 [ 23   7 149]
 [132   1  14]]
[[132   1  14]
 [ 12 159   3]
 [ 23   7 149]]
0.8814828057981043
0.88
```



Another way to do agglomerative clustering using SciPy:
https://docs.scipy.org/doc/scipy/reference/cluster.hierarchy.html

[20]:
```
import scipy.cluster.hierarchy as hr

Z = hr.linkage(X, method='complete', metric='euclidean')

print (Z.shape, X.shape)
```

```
(499, 4) (500, 2)
```

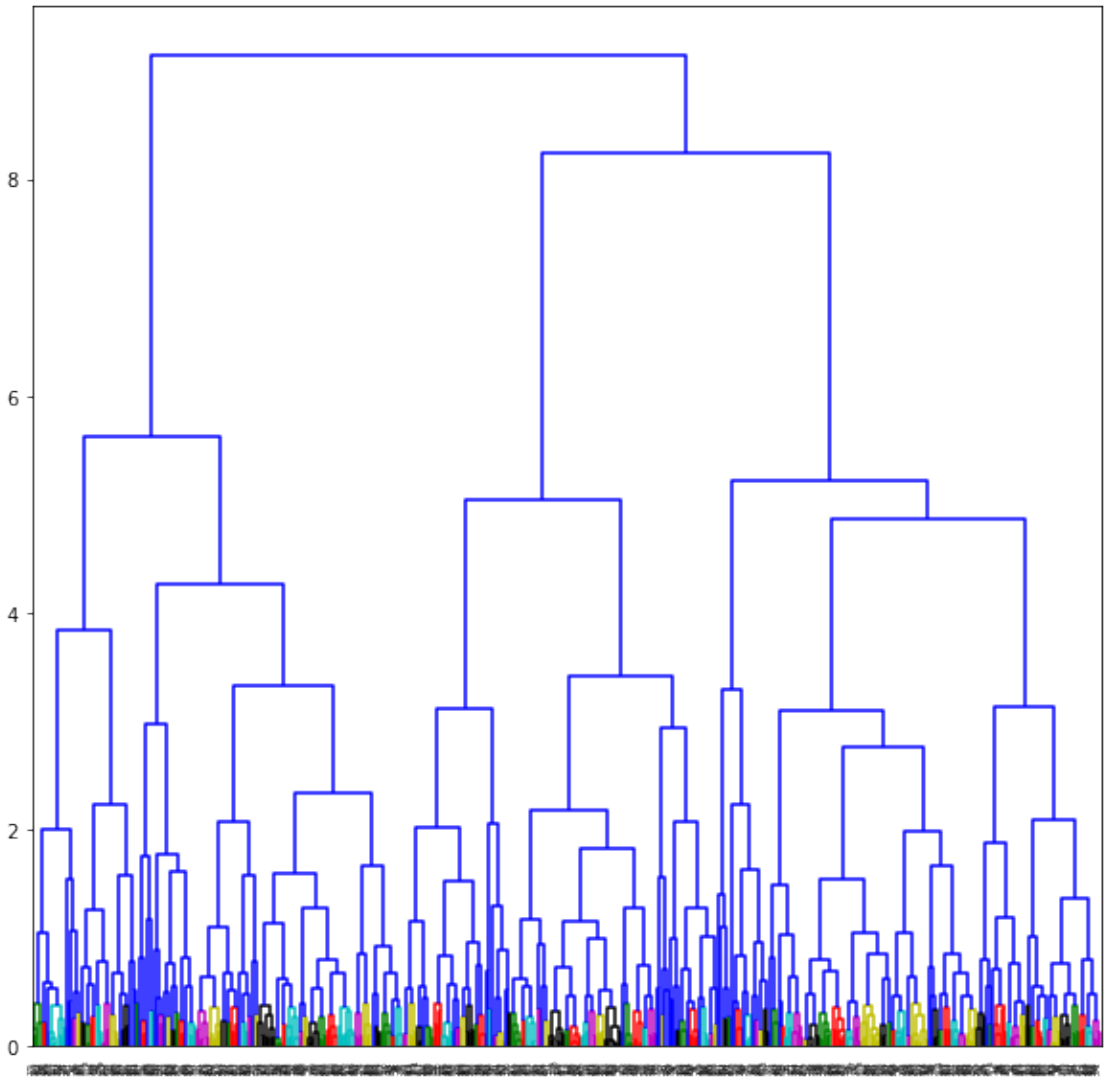
[21]:
```
import scipy.spatial.distance as sp_dist
D = sp_dist.pdist(X, 'euclidean')
Z = hr.linkage(D, method='complete')
print (Z.shape, X.shape)
```

```
(499, 4) (500, 2)
```

Hierarchical clustering returns a 4 by (n-1) matrix Z. At the i-th iteration, clusters with indices Z[i, 0] and Z[i, 1] are combined to form cluster n + i. A cluster with an index less than n corresponds to one of the n original observations. The distance between clusters Z[i, 0] and Z[i, 1] is given by Z[i, 2]. The fourth value Z[i, 3] represents the number of original observations in the newly formed cluster.

[22]:
```
fig = plt.figure(figsize=(10,10))
T = hr.dendrogram(Z,color_threshold=0.4, leaf_font_size=4)
fig.show()
```

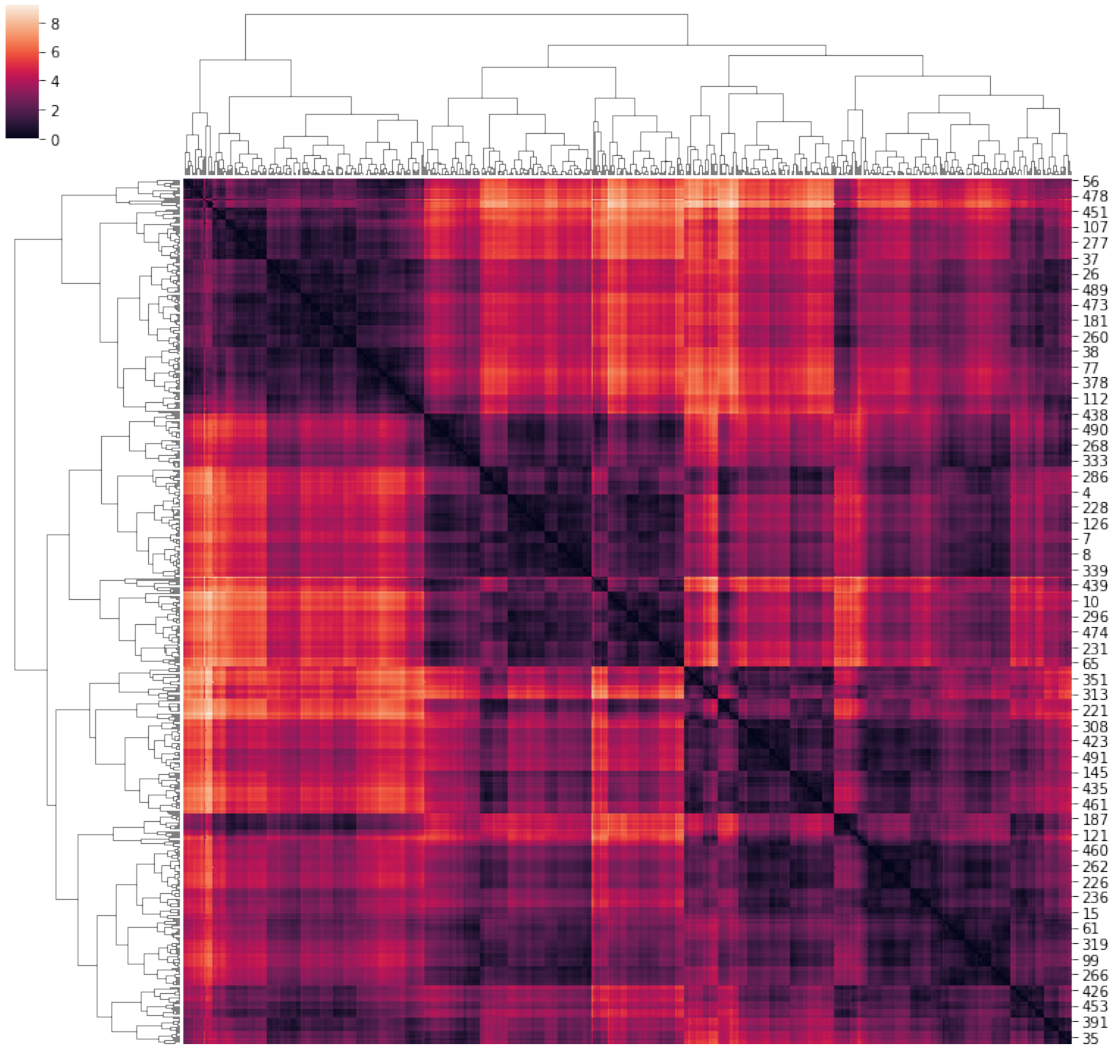
```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning:
Matplotlib is currently using module://ipykernel.pylab.backend_inline, which is
a non-GUI backend, so cannot show the figure.
  This is separate from the ipykernel package so we can avoid doing imports
until
```



Another way to do agglomerative clustering (and visualizing it): http://seaborn.pydata.org/generated/seaborn.clustermap.html

[23]:
```
distances = metrics.euclidean_distances(X)
cg = sns.clustermap(distances, method="complete", figsize=(13,13),␣
 ↪xticklabels=False)
print (cg.dendrogram_col.reordered_ind)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\matrix.py:603:
ClusterWarning: scipy.cluster: The symmetric non-negative hollow observation
matrix looks suspiciously like an uncondensed distance matrix
  metric=self.metric)

[56, 199, 237, 179, 233, 358, 303, 452, 143, 478, 147, 440, 74, 223, 16, 388,
467, 267, 451, 44, 406, 290, 201, 422, 92, 100, 60, 107, 342, 356, 269, 458,
327, 393, 275, 165, 277, 135, 272, 117, 301, 227, 95, 172, 193, 37, 444, 310,
414, 279, 332, 57, 484, 21, 26, 46, 350, 184, 488, 192, 264, 340, 78, 489, 66,
178, 448, 220, 408, 160, 180, 499, 473, 130, 36, 22, 150, 34, 133, 177, 118,
181, 436, 109, 307, 380, 76, 241, 263, 455, 260, 167, 295, 446, 470, 169, 316,
400, 462, 38, 62, 242, 334, 476, 250, 417, 243, 402, 77, 321, 196, 475, 257, 85,
361, 67, 377, 378, 413, 481, 115, 323, 431, 63, 357, 206, 112, 471, 335, 105,
482, 212, 280, 205, 211, 438, 183, 96, 443, 447, 2, 55, 329, 291, 490, 379, 249,
374, 114, 120, 450, 87, 163, 268, 30, 287, 25, 119, 128, 441, 219, 311, 333, 13,
88, 302, 337, 348, 93, 479, 141, 286, 483, 363, 411, 234, 486, 170, 200, 309, 4,
457, 463, 382, 124, 373, 82, 421, 176, 228, 164, 248, 48, 288, 162, 318, 235,
459, 126, 370, 182, 190, 213, 466, 396, 11, 116, 7, 75, 376, 445, 246, 70, 353,
18, 198, 8, 341, 368, 305, 292, 298, 485, 29, 247, 339, 175, 389, 27, 254, 407,
424, 49, 216, 439, 281, 464, 102, 271, 371, 54, 123, 492, 10, 195, 23, 171, 397,
245, 428, 89, 101, 296, 137, 204, 142, 255, 354, 384, 73, 317, 474, 1, 258, 189,
251, 132, 362, 12, 218, 231, 418, 209, 40, 86, 136, 404, 352, 349, 65, 84, 208,
47, 324, 430, 149, 104, 229, 351, 45, 394, 285, 293, 224, 31, 225, 140, 313, 42,
17, 217, 381, 359, 383, 33, 412, 221, 312, 325, 442, 152, 72, 240, 108, 174,
308, 80, 367, 194, 5, 186, 0, 106, 365, 423, 344, 449, 433, 41, 91, 215, 210,
173, 491, 58, 127, 369, 297, 315, 392, 153, 437, 145, 304, 71, 168, 111, 110,
364, 410, 52, 435, 203, 32, 498, 336, 306, 469, 256, 416, 461, 81, 155, 386,
429, 129, 415, 43, 496, 187, 330, 355, 154, 497, 395, 495, 282, 331, 121, 494,
79, 300, 372, 276, 244, 487, 425, 460, 19, 103, 345, 273, 434, 283, 480, 166,
262, 253, 328, 50, 83, 69, 420, 493, 53, 226, 347, 360, 146, 265, 398, 432, 326,
24, 236, 125, 238, 51, 239, 131, 385, 151, 320, 15, 139, 159, 401, 456, 6, 322,
468, 188, 61, 98, 68, 387, 472, 294, 232, 390, 261, 319, 28, 90, 97, 427, 122,
375, 14, 314, 99, 191, 230, 134, 197, 252, 158, 214, 156, 266, 94, 274, 338,
409, 113, 465, 20, 64, 426, 343, 3, 144, 9, 202, 284, 405, 138, 453, 161, 399,
299, 148, 270, 185, 222, 259, 391, 59, 278, 157, 366, 346, 454, 289, 477, 35,
39, 419, 207, 403]
```



1.3.3 DBSCAN Algorithm

More on DBSCAN here: http://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html

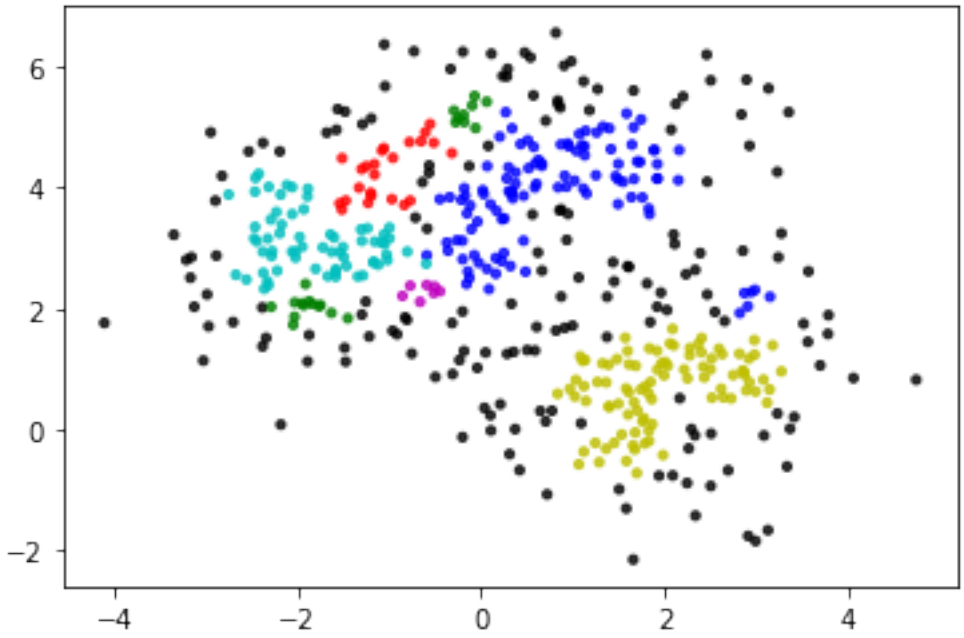
[24]:
```
dbscan = sk_cluster.DBSCAN(eps=0.3)
dbscan_labels = dbscan.fit_predict(X)
print(dbscan_labels) #label -1 corresponds to noise
renamed_dbscan_labels = [x+1 for x in dbscan_labels]
C = metrics.confusion_matrix(renamed_dbscan_labels,true_labels)
print (C[:,:max(true_labels)+1])
#print(metrics.confusion_matrix(true_labels,renamed_dbscan_labels))
```

```
[ 0  3  1 -1  2  0 -1  2  3  6  3  2 -1  4  0 -1 -1 -1  3  0 -1  5  5  3
  6  7  5 -1  0  3  7 -1  9 -1  5 -1  5  5  5 -1  3  0 -1  8 -1 -1  5 -1
  3 -1  0  0  0  0 -1  1 -1  5  0 -1 -1  0  5  5 -1 -1 -1  5  0  0  3 -1
```

```
 -1   3 -1   2   5   5   5 -1 -1 -1   3   0 -1 -1   3 -1   4   3   0   0 -1 -1   0   5
 -1   0   0   0 -1   3 -1   0 -1 -1   0 -1   0   5   0   0 -1   0   1   5   2   5   5   7
  1 -1   0 -1   3   6   3   0 -1 -1   5   0   3   5   0   5   3   3 -1 -1 -1   2   3 -1
 -1   0   0 -1 -1 -1   5 -1 -1   0   8 -1   0 -1   0 -1   5 -1   1   1   3   5   0   5
  2   5   2   3   5   0   0   2   3   5   5 -1   5   5   3 -1   5 -1   0   8   0   3   3   0
  5   5   0   3   5   0   3   5   2 -1   6   9   3 -1 -1 -1 -1   3   0 -1 -1   3   3   0
 -1 -1   1   4   5 -1 -1 -1 -1 -1   0   5   3 -1   0   3   0 -1   2   3   6   5   0   0
 -1   5   5   5   0   3   3   3   3   1   5   3   3   0 -1   3   9 -1   3 -1   5   0   0   5
  5   0   0 -1   7   5 -1 -1   5   0   0   5   0   5 -1   5 -1 -1 -1   0 -1 -1   2   7
  3 -1 -1   1   3 -1   0   5   3   0   3 -1 -1   5   4 -1 -1   3   9   5   0   2   5   4
 -1 -1   0   0   5   3   3   0 -1   5   0   5 -1 -1   6   5   0   1   8 -1   5   4   5 -1
  9   4   0   2   5   3   5 -1   0   0 -1   0 -1 -1   5 -1 -1   3   3 -1   5   5 -1 -1
  0 -1   3   2   0   0 -1   0   3   0   3 -1 -1   3   1   0   2   5   5   1   5 -1   3 -1
  3   0 -1   0 -1   2   0 -1   0   5 -1 -1   2 -1   6 -1   5 -1   5 -1   3 -1   5 -1
  5   0   9   2 -1   5   5   0   9   5   3 -1   0   3 -1   0 -1   0 -1   0 -1 -1 -1   5
  6   0   0   0   5   0 -1 -1 -1 -1 -1 -1   5   2   5 -1 -1   0 -1 -1 -1 -1 -1   5
  0   2   5   3   0 -1 -1   2 -1   0   3 -1 -1   9   5 -1   0   5   3 -1   5 -1 -1 -1
  0   5 -1   2   5   3   2   0   5   5   1   0 -1   0 -1 -1   8   8   9   5]
[[58 68 41]
 [87  0 15]
 [ 0  0 13]
 [ 6  0 18]
 [ 0  0 66]
 [ 0  0  7]
 [ 0 92  1]
 [ 7  1  0]
 [ 0  0  5]
 [ 0  6  0]
 [ 9  0  0]]
```

[25]:
```
#colors = np.array([x for x in 'bgrcmykbgrcmykbgrcmykbgrcmyk'])
#colors = np.hstack([colors] * 20)
colors = np.array([x for x in 'bgrcmywk'*10])
plt.scatter(X[:, 0], X[:, 1], color=colors[dbscan_labels].tolist(), s=10,␣
 ↪alpha=0.8)
```

[25]:
```
<matplotlib.collections.PathCollection at 0x2b6f8ee56a0>
```



1.4 Dimensionality Reduction

We can do dimensionality reduction and PCA using the sklearn library

[26]:
```
import sklearn.datasets as sk_data

data = sk_data.make_low_rank_matrix(n_samples=100, n_features=50,␣
 ↪effective_rank=2, tail_strength=0.0, random_state=None)
```

[27]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
data2 = pca.fit_transform(data)
print(data2.shape)
```

```
(100, 2)
```

2 Processing Complex Data

So far we have assumed that the intput is in the form of numerical vectors to which we can apply directly the algorithms we have. Often the data will be more complex. For example what if we want to cluster categorical data, itemsets, or text? Python provides libraries for processing the data and transforming them to a format that we can use.

Python offers a set of tools for extracting features:http://scikit-learn.org/stable/modules/feature_extraction.html

2.0.1 DictVectorizer

The DictVectorizer feature extraction: http://scikit-learn.org/stable/modules/generated/sklearn.feature_extrac

The DictVectorizer takes a dictionary of attribute-value pairs and transforms them into numerical vectors. Real values are preserved, while categorical attributes are transformed into binary. The vectorizer produces a *sparse representation*.

[17]:
```
measurements = [
{'city': 'Dubai', 'temperature': 45},
{'city': 'London', 'temperature': 12},
{'city': 'San Fransisco', 'temperature': 23},
]
from sklearn.feature_extraction import DictVectorizer
vec = DictVectorizer()
print(type(vec.fit_transform(measurements)))
print(vec.fit_transform(measurements).toarray())
vec.get_feature_names()
```

```
<class 'scipy.sparse.csr.csr_matrix'>
[[ 1.  0.  0. 45.]
 [ 0.  1.  0. 12.]
 [ 0.  0.  1. 23.]]
```

[17]:
```
['city=Dubai', 'city=London', 'city=San Fransisco', 'temperature']
```

[30]:
```
measurements = [
    {'refund' : 'No','marital_status': 'married', 'income' : 100},
    {'refund' : 'Yes','marital_status': 'single', 'income' : 120},
    {'refund' : 'No','marital_status':'divorced', 'income' : 80},
]
vec = DictVectorizer()
print(vec.fit_transform(measurements))
vec.get_feature_names()
```

```
  (0, 0)        100.0
  (0, 2)        1.0
  (0, 4)        1.0
  (1, 0)        120.0
  (1, 3)        1.0
  (1, 5)        1.0
  (2, 0)        80.0
  (2, 1)        1.0
  (2, 4)        1.0
```

[30]:
```
['income',
 'marital_status=divorced',
 'marital_status=married',
 'marital_status=single',
 'refund=No',
```

```
 'refund=Yes']
```

2.0.2 Text processing

Feature extraction from text: http://scikit-learn.org/stable/modules/classes.html#text-feature-extraction-ref

SciKit datasets: http://scikit-learn.org/stable/datasets/

We will use the 20-newsgroups datasets which consists of postings on 20 different newsgroups.

More information here: http://scikit-learn.org/stable/datasets/#the-20-newsgroups-text-dataset

[31]:
```
from sklearn.datasets import fetch_20newsgroups

categories = ['comp.os.ms-windows.misc', 'sci.space','rec.sport.baseball']
#categories = ['alt.atheism', 'sci.space','rec.sport.baseball']
news_data = sk_data.fetch_20newsgroups(subset='train',
                                remove=('headers', 'footers', 'quotes'),
                                categories=categories)
print (news_data.target)
print (len(news_data.target))
```

```
[2 0 0 ... 2 1 2]
1781
```

[23]:
```
print (type(news_data))
print (news_data.filenames)
print (news_data.target[:10])
print (news_data.data[1])
print (len(news_data.data))
```

```
<class 'sklearn.utils.Bunch'>
['C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\sci.space\\60940'
 'C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\comp.os.ms-windows.misc\\9955'
 'C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\comp.os.ms-windows.misc\\9846'
 ...
 'C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\sci.space\\60891'
 'C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\rec.sport.baseball\\104484'
 'C:\\Users\\tsapa\\scikit_learn_data\\20news_home\\20news-bydate-
train\\sci.space\\61110']
[2 0 0 2 0 0 1 2 2 1]
Recently the following problem has arrisen.  The first time I turn on my
computer when windows starts (from my autoexec) after the win31 title screen
```

```
the computer reboots on its own.  Usually the second time (after reboot) or
from the DOS prompt everything works fine.

 s far as I remember I have not changed my config.sys or autoxec.bat or
win.ini.  I can't remember whether this problem occured before I
optimized/defragmented my disk and created a larger swap file (Thank you
MathCAD 4 :(  )

System 386sx, 4MB, stacker 2.0, win31, DOS 5

---
------------------------------------------------------------------------
1781
```

2.0.3 CountVectorizer

The CountVectorizer can be used to extract features in the form of bag of words. It is typically used for text, but you could use it to represent also a collection of itemsets (where each itemset will become a word).

[32]:
```
import sklearn.feature_extraction.text as sk_text

corpus = ['This is the first document.',
          'this is the second second document.',
          'And the third one.',
          'Is this the first document?',
         ]

vectorizer = sk_text.CountVectorizer(min_df=1)
X = vectorizer.fit_transform(corpus)
print(X.toarray())
vectorizer.get_feature_names()
```

```
[[0 1 1 1 0 0 1 0 1]
 [0 1 0 1 0 2 1 0 1]
 [1 0 0 0 1 0 1 1 0]
 [0 1 1 1 0 0 1 0 1]]
```

[32]:
```
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
```

[19]:
```
vectorizer = sk_text.CountVectorizer(min_df=1,stop_words = 'english')

X2 = vectorizer.fit_transform(corpus)
print(X2.toarray())
vectorizer.get_feature_names()
```

```
[[1 0]
 [1 2]
```

```
 [0 0]
 [1 0]]
```

[19]:
```
['document', 'second']
```

2.0.4 TfIdfVectorizer

TfIdfVectorizer transforms text into a sparse matrix where rows are text and columns are words, and values are the tf-dif values. It performs tokenization, normalization, and removes stop-words. More here: http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html#sklearn.feature_extra

[33]:
```
vectorizer = sk_text.TfidfVectorizer(min_df=1)
X = vectorizer.fit_transform(corpus)
print(X.toarray())
print (vectorizer.get_feature_names())
```

```
[[0.         0.43877674 0.54197657 0.43877674 0.         0.
  0.35872874 0.         0.43877674]
 [0.         0.27230147 0.         0.27230147 0.         0.85322574
  0.22262429 0.         0.27230147]
 [0.55280532 0.         0.         0.         0.55280532 0.
  0.28847675 0.55280532 0.        ]
 [0.         0.43877674 0.54197657 0.43877674 0.         0.
  0.35872874 0.         0.43877674]]
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
```

Removing stop-words

[37]:
```
vectorizer = sk_text.TfidfVectorizer(stop_words = 'english',min_df=1)
X = vectorizer.fit_transform(corpus)
print(X.toarray())
print (vectorizer.get_feature_names())
```

```
[[1.         0.        ]
 [0.30403549 0.9526607 ]
 [0.         0.        ]
 [1.         0.        ]]
['document', 'second']
```

[35]:
```
vectorizer = sk_text.TfidfVectorizer(stop_words='english',
                                     #max_features = 1000,
                                     min_df=4, max_df=0.8)
data = vectorizer.fit_transform(news_data.data)
print(type(data))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

2.1 Clustering text data

An example of what we want to do: http://scikit-learn.org/stable/auto_examples/text/document_clustering.ht

[36]:
```
import sklearn.cluster as sk_cluster
k=3
kmeans = sk_cluster.KMeans(n_clusters=k, init='k-means++', max_iter=100,␣
 ↪n_init=1)
kmeans.fit_predict(data)
```

[36]:
```
array([0, 2, 2, ..., 0, 0, 0])
```

[37]:
```
print("Top terms per cluster:")
asc_order_centroids = kmeans.cluster_centers_.argsort()#[:, ::-1]
order_centroids = asc_order_centroids[:,::-1]
terms = vectorizer.get_feature_names()
for i in range(k):
    print ("Cluster %d:" % i)
    for ind in order_centroids[i, :10]:
        print (' %s' % terms[ind])
    print
```

```
Top terms per cluster:
Cluster 0:
 space
 like
 just
 nasa
 think
 know
 don
 thanks
 does
 people
Cluster 1:
 year
 team
 game
 games
 think
 baseball
 runs
 good
 hit
 players
Cluster 2:
 windows
 file
 dos
 files
```

```
use
thanks
drivers
card
driver
problem
```

[38]:
```
C = metrics.confusion_matrix(kmeans.labels_,news_data.target)

mapped_kmeans_labels,C = cluster_class_mapping(kmeans.labels_,news_data.target)
print (C)
p = metrics.precision_score(news_data.target,mapped_kmeans_labels, average=None)
print(p)
r = metrics.recall_score(news_data.target,mapped_kmeans_labels, average = None)
print(r)
```

```
[[380   1 210]
 [  0 422 175]
 [  1   3 589]]
[ 0.99737533  0.99061033  0.60472279]
[ 0.642978    0.70686767  0.99325464]
```

[39]:
```
agglo = sk_cluster.AgglomerativeClustering(linkage = 'complete', n_clusters =␣
 ↪3,)
dense = data.todense()
agglo_labels = agglo.fit_predict(dense) # agglomerative needs dense data

C_agglo= metrics.confusion_matrix(news_data.target,agglo_labels)
print (C_agglo)
```

```
[[171 400  20]
 [156 438   3]
 [250 340   3]]
```

[40]:
```
dbscan = sk_cluster.DBSCAN(eps=0.1)
dbscan_labels = dbscan.fit_predict(data)
C = metrics.confusion_matrix(news_data.target,dbscan.labels_)
print (C)
```

```
[[  0   0   0   0]
 [556   9  26   0]
 [567   0  30   0]
 [576   0  17   0]]
```