Name: Joyce Le ID#: 82549113 UCI NetID: lejy

# CS 178 Homework 5

### **Problem 1: Clustering**

```
In [1]:
         import numpy as np
         import mltools as ml
         import matplotlib.pyplot as plt
In [2]: print('1)')
         # Load data
         iris = np.genfromtxt("data/iris.txt",delimiter=None)
         X = iris[:,0:2]
         Y = iris[:,-1]
         # select first two features and plot them
         plt.figure()
         plt.scatter(X[:, 0], X[:, 1])
         plt.show()
         1)
          4.5
          4.0
          3.5
          3.0
          2.5
          2.0
                4.5
                      5.0
                            5.5
                                  6.0
                                       6.5
                                             7.0
                                                   7.5
                                                         8.0
```

The data does look to be clustered. I think two clusters exist because the data for these two clusters seem to be nicely divided. There could also possibly be another third cluster at the bottom beccause the bottom cluster is quite large.

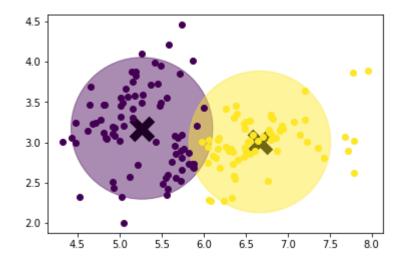
```
In [3]: print('2)\n')
print('k=2:\n')

ssd_best = np.inf
for i in range(5):
    Z_i, mu_i, ssd_i = ml.cluster.kmeans(X, K=2, init='k++', max_iter=5)
    print(ssd_i)
    # different initializations do NOT all find the same solution
    # pick best one
    if ssd_i < ssd_best:
        Z, mu, ssd_best = Z_i, mu_i, ssd_i
ml.plotClassify2D(None,X,Z)
plt.scatter(mu[:, 0], mu[:, 1], s=400, marker='x', facecolor='black', lw=8)
plt.scatter(mu[:, 0], mu[:, 1], s=20000, alpha=.45, c=np.unique(Z))

2)
k=2:</pre>
```

57.87966196118197 57.87966196118197 57.87966196118197 58.01355452847487 57.87966196118197

Out[3]: <matplotlib.collections.PathCollection at 0x21d89d58860>



```
In [4]: print('k=5:\n')

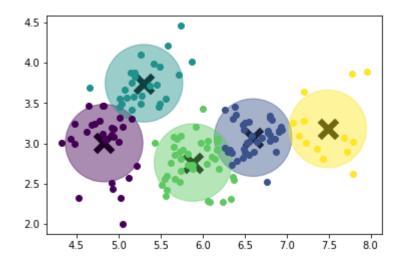
ssd_best = np.inf
for i in range(5):
    Z_i, mu_i, ssd_i = ml.cluster.kmeans(X, K=5, init='k++', max_iter=5)
    print(ssd_i)
    # different initializations do NOT all find the same solution
    # pick best one
    if ssd_i < ssd_best:
        Z, mu, ssd_best = Z_i, mu_i, ssd_i

ml.plotClassify2D(None,X,Z)
plt.scatter(mu[:, 0], mu[:, 1], s=300, marker='x', facecolor='black', lw=6)
plt.scatter(mu[:, 0], mu[:, 1], s=6000, alpha=.45, c=np.unique(Z))</pre>
```

#### k=5:

- 21.325838512733114
- 20.90559762715885
- 28.963012289610635
- 25.109620287979148
- 21.567280736715215

Out[4]: <matplotlib.collections.PathCollection at 0x21d89c86208>



```
In [5]: print('k=20:\n')

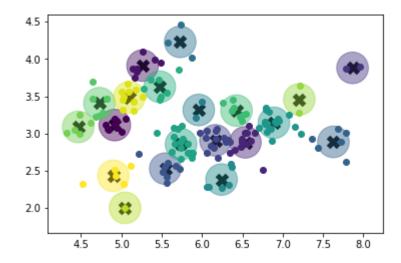
ssd_best = np.inf
for i in range(5):
    Z_i, mu_i, ssd_i = ml.cluster.kmeans(X, K=20, init='k++', max_iter=5)
    print(ssd_i)
    # different initializations do NOT all find the same solution
    # pick best one
    if ssd_i < ssd_best:
        Z, mu, ssd_best = Z_i, mu_i, ssd_i

ml.plotClassify2D(None,X,Z)
plt.scatter(mu[:, 0], mu[:, 1], s=100, marker='x', facecolor='black', lw=5)
plt.scatter(mu[:, 0], mu[:, 1], s=1000, alpha=.45, c=np.unique(Z))</pre>
```

#### k=20:

- 4.4800293480559255
- 4.513257894284805
- 4.258703733850255
- 5.282172698257471
- 4.1895286826698515

Out[5]: <matplotlib.collections.PathCollection at 0x21d89e05fd0>

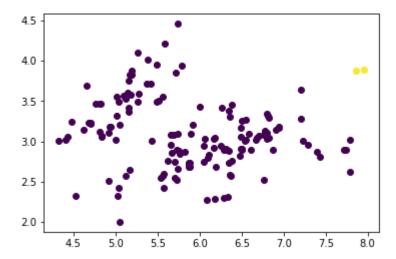


```
In [6]: print('3)')

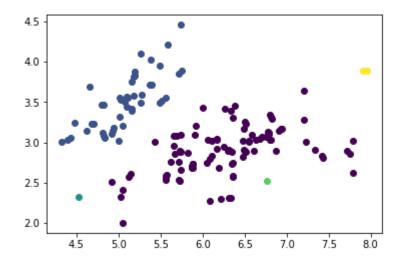
# single Linkage
for k in [2,5,20]:
    print('Single linkage, k =', k)
    Z, dendogram = ml.cluster.agglomerative(X, K=k, method='min')
    plt.figure()
    ml.plotClassify2D(None,X,Z)
    plt.show()

# complete Linkage
for k in [2,5,20]:
    print('Complete linkage, k =', k)
    Z, dendogram = ml.cluster.agglomerative(X, K=k, method='max')
    plt.figure()
    ml.plotClassify2D(None,X,Z)
    plt.show()
```

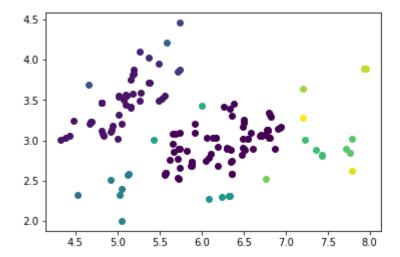
3)
Single linkage, k = 2



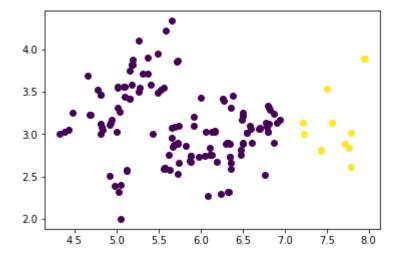
Single linkage, k = 5



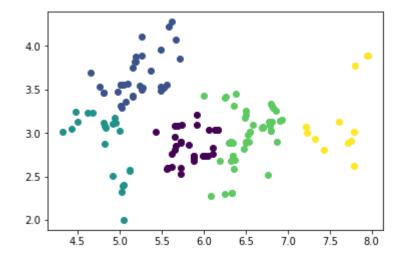
Single linkage, k = 20



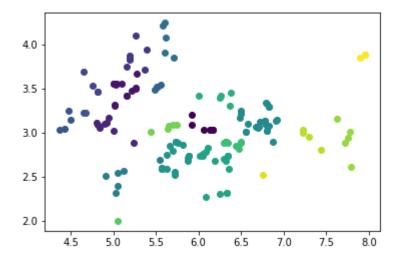
Complete linkage, k = 2



Complete linkage, k = 5



Complete linkage, k = 20

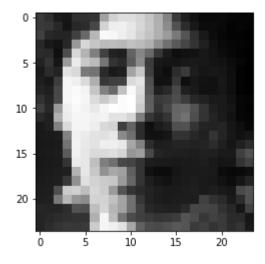


4) K-means is different from agglomerative because k-means produces clusters that are more circular and similar to each other. Agglomerative clustering forms clusters that are differently shaped and sized according to each data cluster. This is more true for single-linkage agglomerative clustering than it is complete linkage. The similarities are that k-means clustering is similar to complete-linkage agglomerative clustering.

#### **Problem 2: EigenFaces**

```
In [7]: X = np.genfromtxt("data/faces.txt", delimiter=None) # load face dataset
plt.figure()
# pick a data point i for display
img = np.reshape(X[i,:],(24,24)) # convert vectorized data to 24x24 image p
atches
plt.imshow( img.T , cmap="gray") # display image patch; you may have to squ
int
```

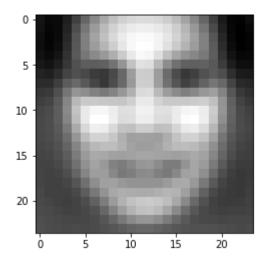
Out[7]: <matplotlib.image.AxesImage at 0x21d8a1628d0>



```
In [8]: print('1)')

mu = X.mean(axis=0)
X_0 = X - mu
plt.figure()
img = np.reshape(mu, (24,24))
plt.imshow(img.T, cmap='gray')
1)
```

Out[8]: <matplotlib.image.AxesImage at 0x21d9a384e48>

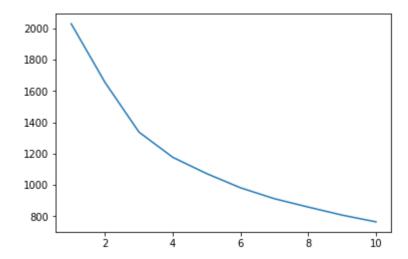


```
In [9]: print('2)')
import scipy.linalg

u,s,v = scipy.linalg.svd(X_0, full_matrices=False)
w = u.dot(np.diag(s))
print('W shape:', w.shape)
print('V shape:', v.shape)
2)
```

W shape: (4916, 576) V shape: (576, 576)

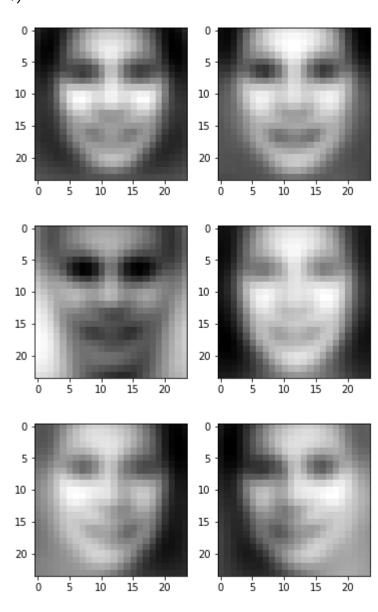
Out[10]: [<matplotlib.lines.Line2D at 0x21d8a132128>]



```
In [11]: print('4)')

for j in range(3):
    a = 2*np.median(np.abs(w[:,j]))
    plus = np.reshape(mu + a*v[j,:], (24,24))
    minus = np.reshape(mu - a*v[j,:], (24,24))
    f,ax = plt.subplots(1,2)
    ax[0].imshow(plus.T, cmap='gray')
    ax[1].imshow(minus.T, cmap='gray')
```

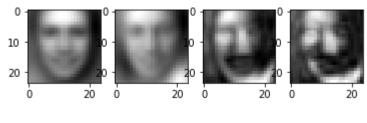
4)

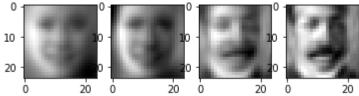


```
In [12]: print('5)')

for i in range(2):
    f,ax = plt.subplots(1,4)
    for j,k in enumerate([5,10,50,100]):
        image = np.reshape(mu + w[i,0:k].dot(v[0:k,:]), (24,24))
        ax[j].imshow(image.T, cmap='gray')
```

5)

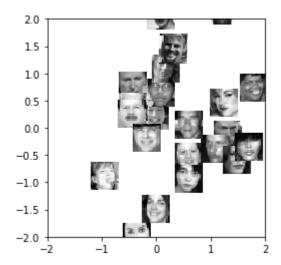




```
In [14]: print('6)')
    idx = np.random.randint(X.shape[0]-1, size=25)

import mltools.transforms
    coord,params = ml.transforms.rescale( w[:,0:2] ) # normalize scale of "W" l
    ocations
    plt.figure();
    for i in idx:
        # compute where to place image (scaled W values) & size
        loc = (coord[i,0],coord[i,0]+0.5, coord[i,1],coord[i,1]+0.5)
        img = np.reshape( X[i,:], (24,24) ) # reshape to square
        plt.imshow( img.T , cmap="gray", extent=loc ) # draw each image
        plt.axis( (-2,2,-2,2) ) # set axis to a reasonable scale
```

6)



## **Statement of Collaboration**

I did not collaborate with anyone on this assignment. I only looked on CampusWire for help on how to do some parts of Problem 2.