Lab5

March 9, 2017

1 CS178 LAB 5 WINTER 2017

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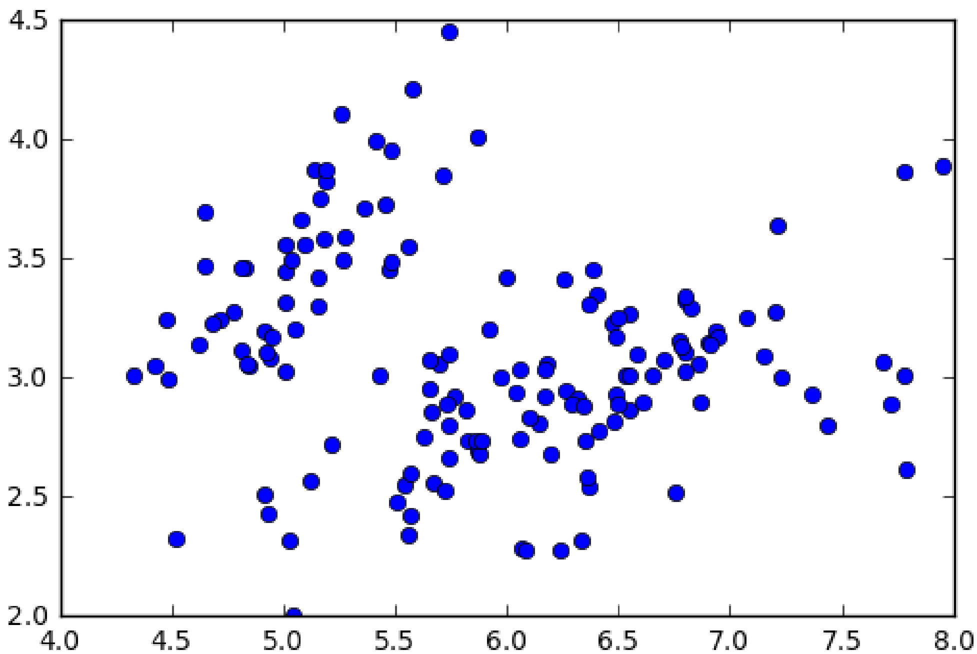
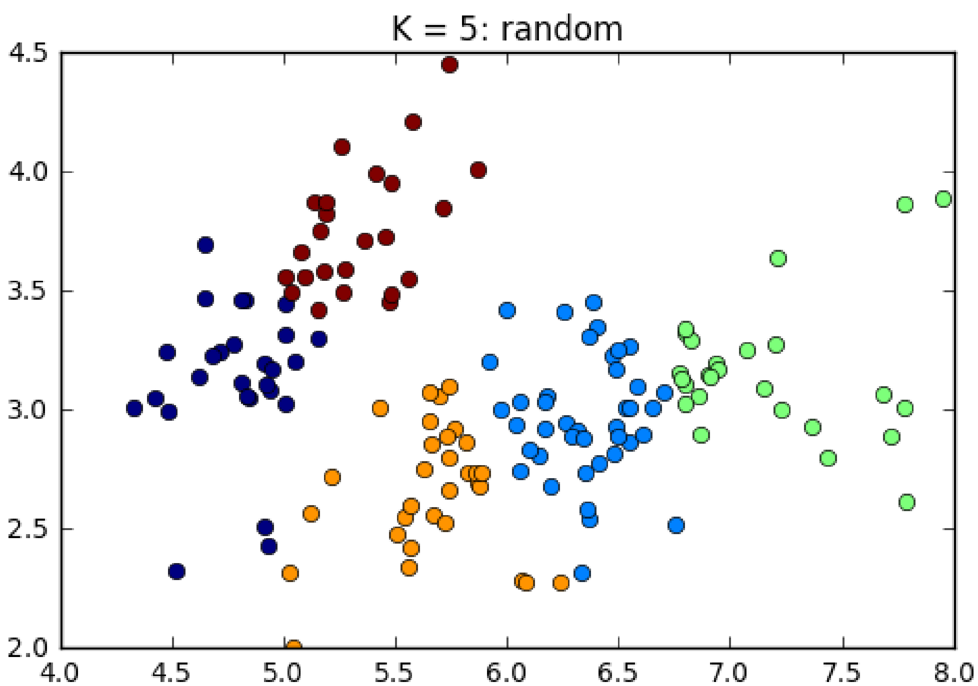
2.0.1 Problem 1A) Basics of clustering: Loading Iris data

```
In [7]: import numpy as np
        import matplotlib.pyplot as plt
        import mltools as ml

        data = np.genfromtxt("C:\Python35\CS178\Lab5\data\iris.txt",delimiter=None)

        X = data[:,0:2]

        plt.plot(X[:,0], X[:,1], 'o')
        plt.show()
```



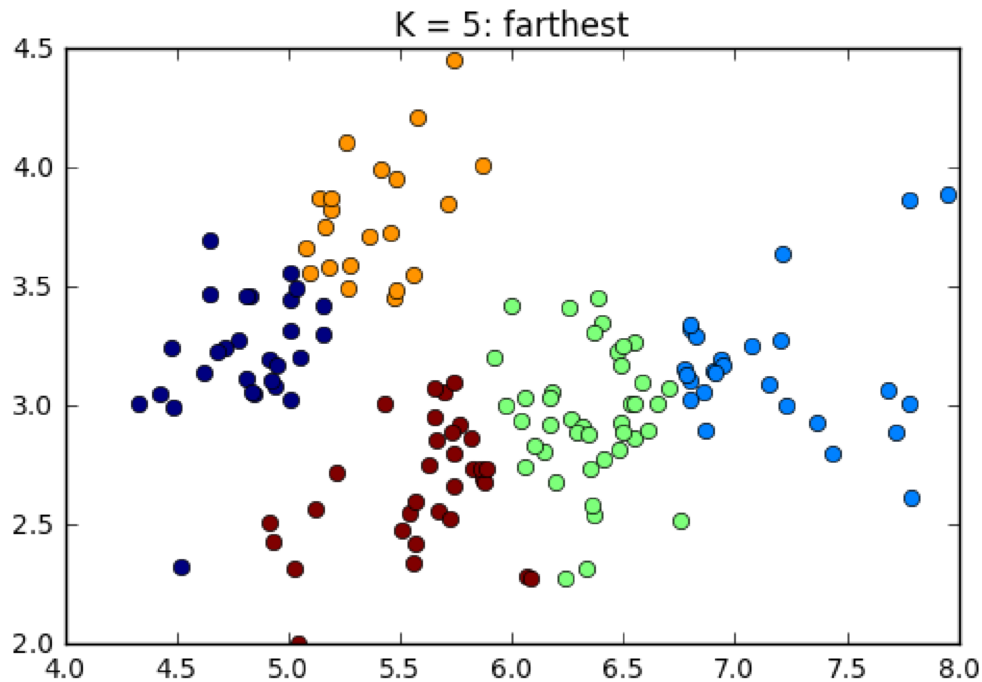
2.0.2 Problem 1B) Basics of clustering: K-means

```
In [23]: kmeans_init = ['random', 'farthest', 'k++']

         # k-mean with k = 5 and k = 20
         for k in [5,20]:

             # different initializations
             for init in kmeans_init:

                 clusters, centers, distance_sum = ml.cluster.kmeans(X, k, init)

                 ml.plotClassify2D(None, X, clusters)

                 plt.title("K = {}: {}".format(k, init))

                 plt.show()

                 print(distance_sum)
```

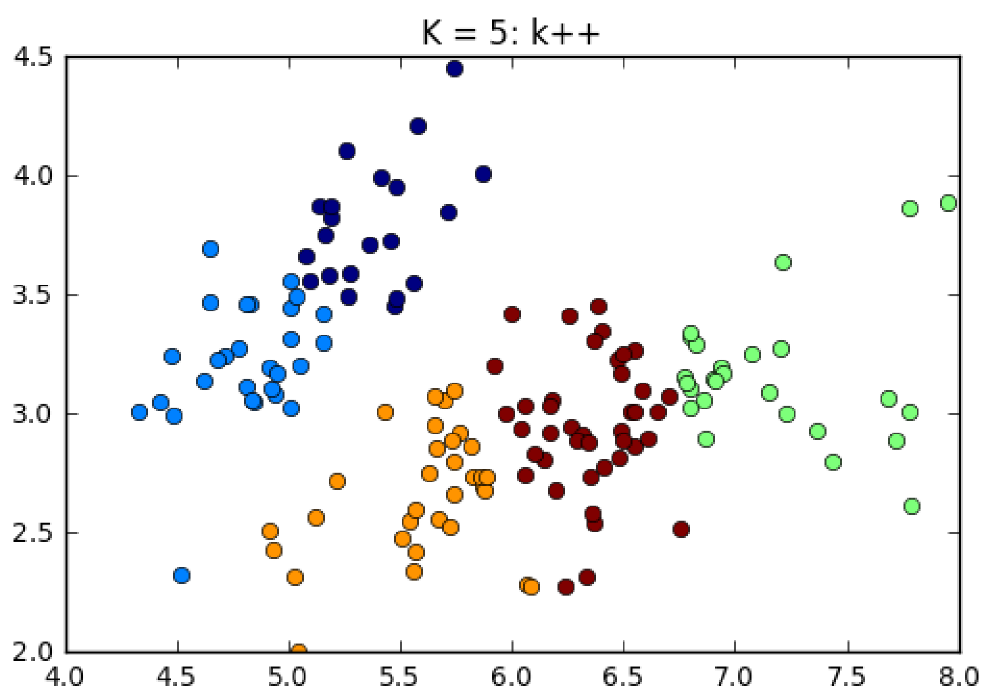



```
21.3288750436
```

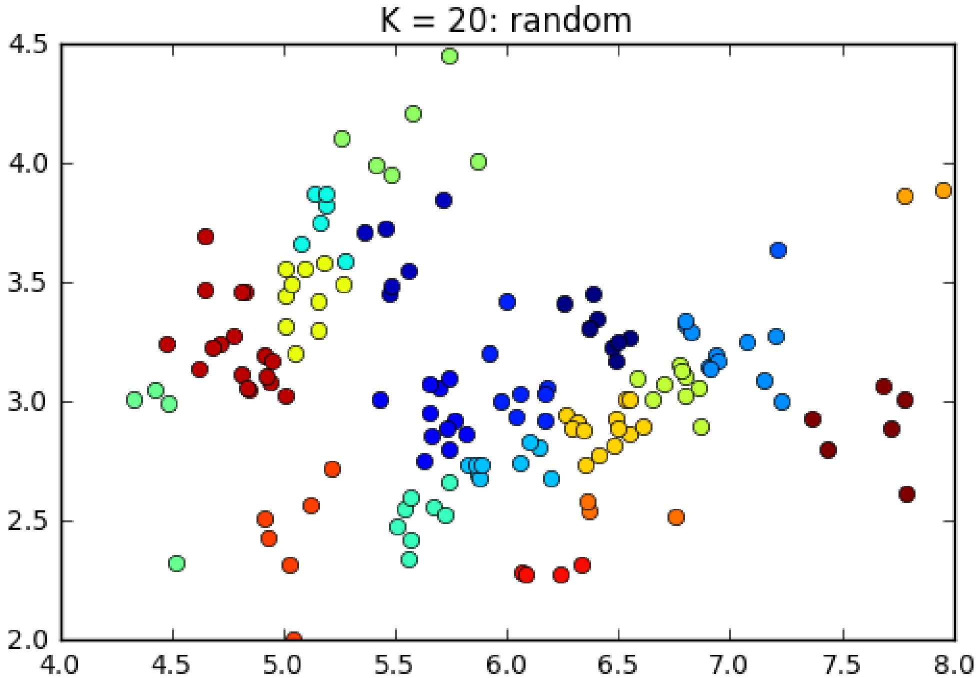
```
C:\Python35\CS178\Lab5\mltools\cluster.py:118: VisibleDeprecationWarning: using a r
  clusters[0,:] = X[np.floor(np.random.rand() * m),:]                          # take
```



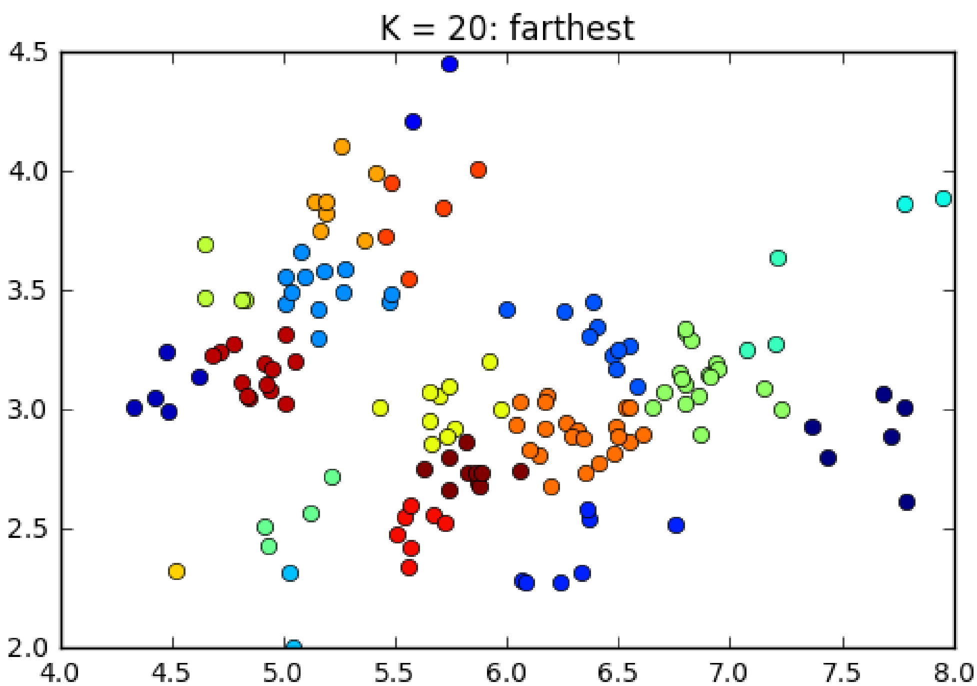
21.341435585



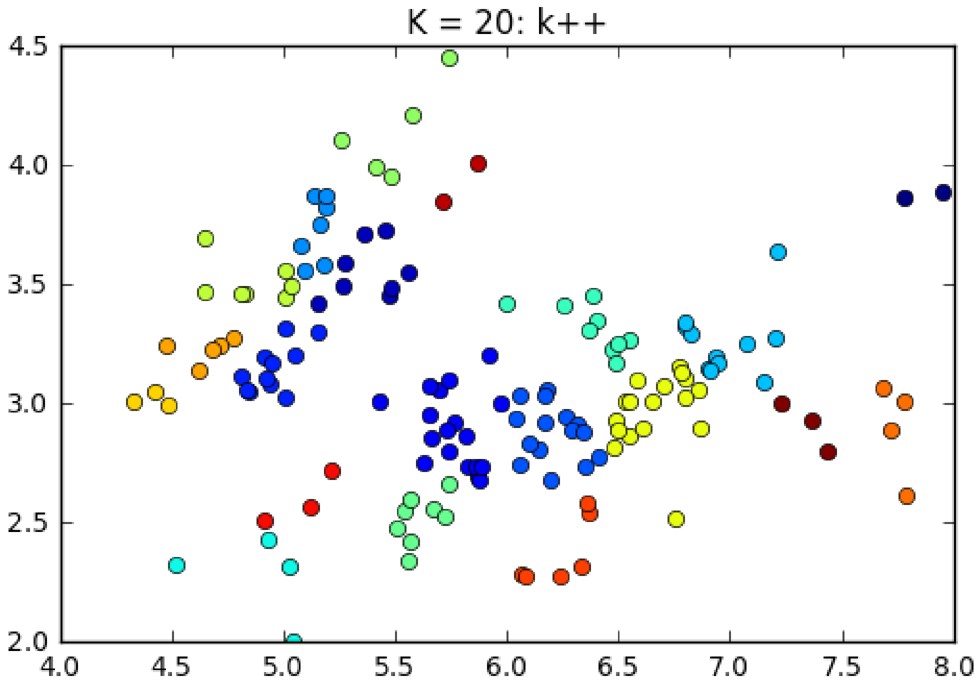
21.341435585



4.65541161813



4.62260455495

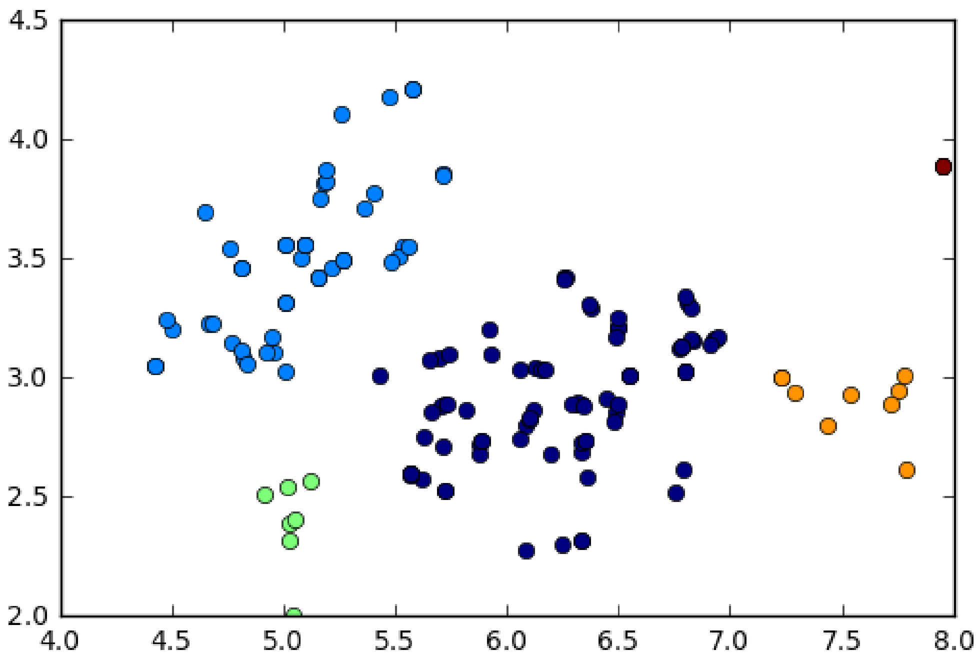


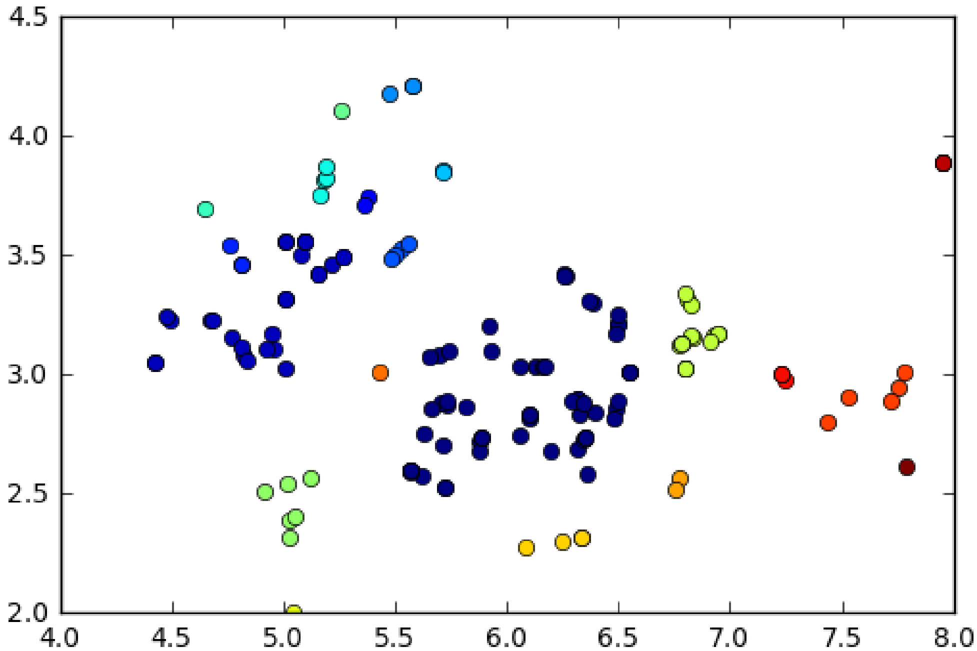
4.54837559628

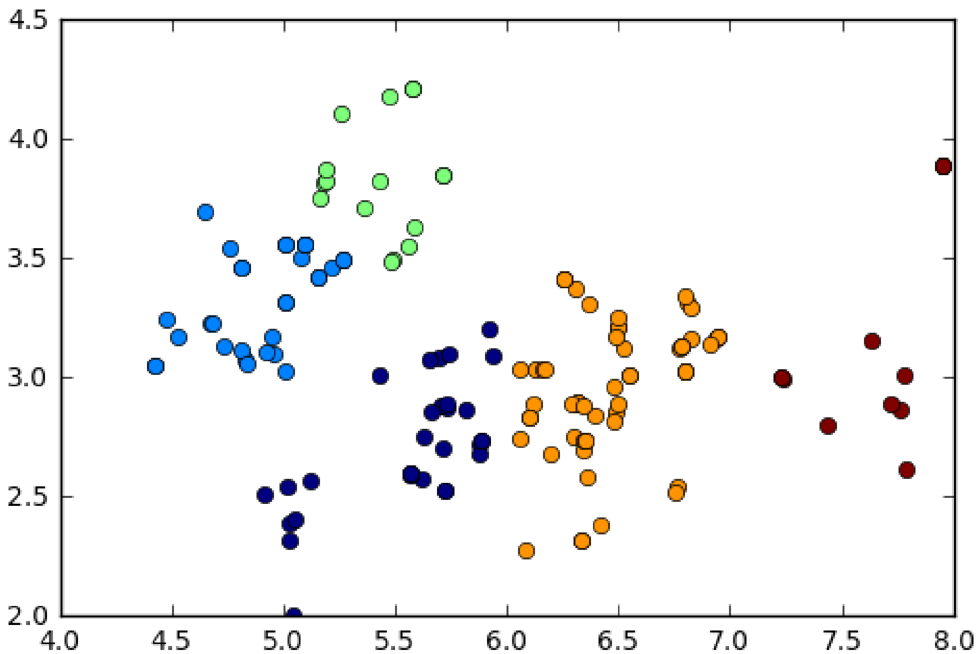
2.0.3 Problem 1C) Basics of clustering: Agglomerative clustering

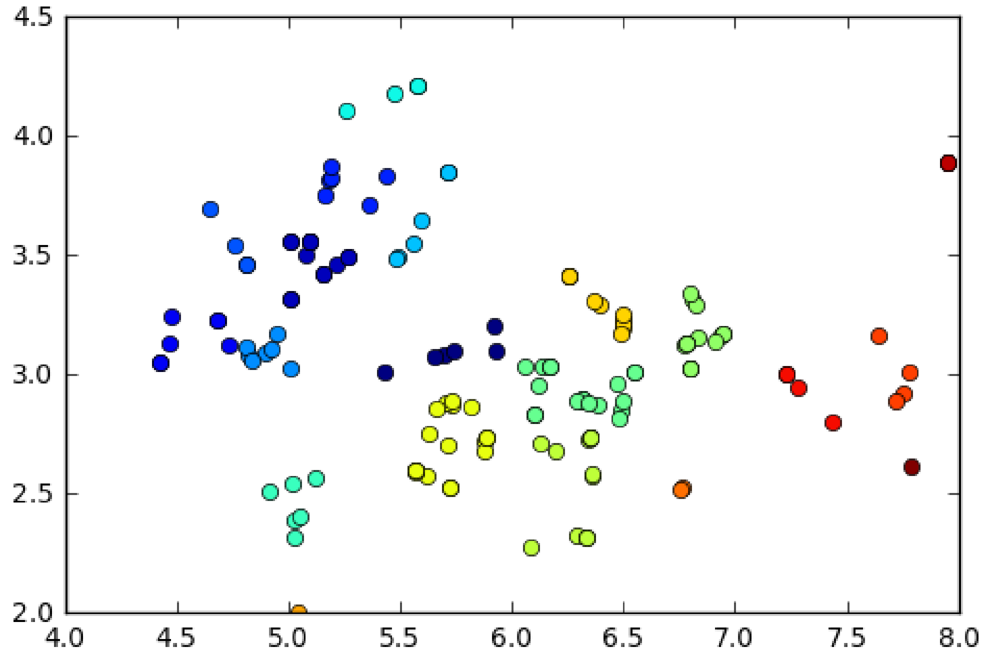
```
In [27]: # Single linkage (minimum distance to center)

         clusters, join = ml.cluster.agglomerative(X, 5, 'min')

         ml.plotClassify2D(None, X, clusters)

         plt.show()

         clusters, join = ml.cluster.agglomerative(X, 20, 'min')

         ml.plotClassify2D(None, X, clusters)

         plt.show()
```

```python
# Complete linkage (maximum distance to center)
clusters, join = ml.cluster.agglomerative(X, 5, 'max')

ml.plotClassify2D(None, X, clusters)

plt.show()

clusters, join = ml.cluster.agglomerative(X, 20, 'max')

ml.plotClassify2D(None, X, clusters)

plt.show()
```




4.5
4.0
3.5
3.0
2.5
2.0
4.0 4.5 5.0 5.5 6.0 6.5 7.0 7.5 8.0


4.5
4.0
3.5
3.0
2.5
2.0
4.0 4.5 5.0 5.5 6.0 6.5 7.0 7.5 8.0



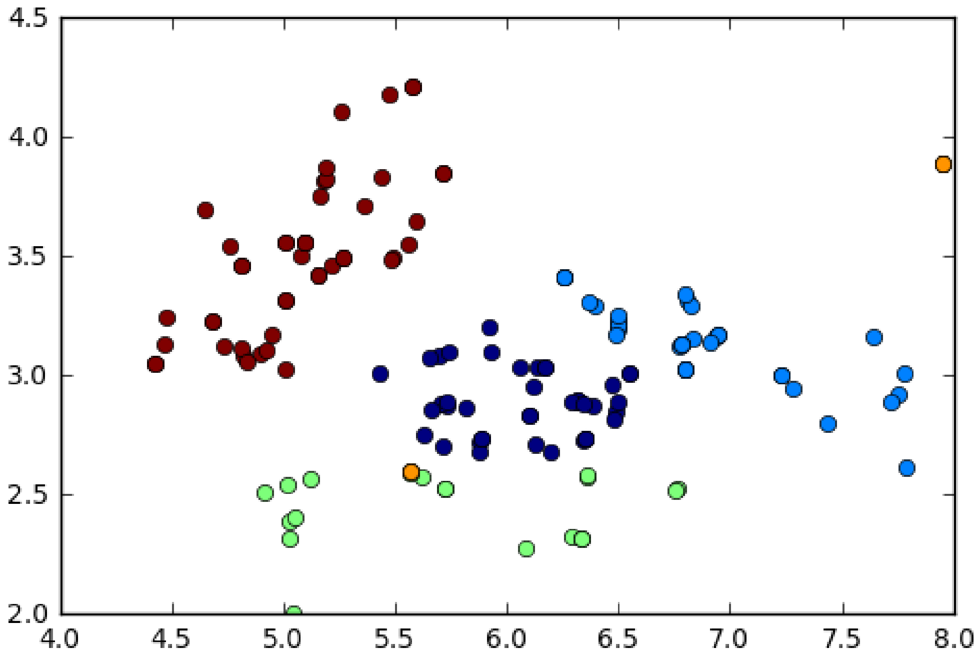
Single linkage for k-means of 5 and 20 looks the most clear cut and reasonable, whereas the complete linkage creates tons of small and separate clusters, which may be better for larger data sets but not this one.

The agglomerative single linkage for k = 20 looks very much like kmeans for k = 5 and both complete linkage graphs resemble the random k = 20 kmeans graph.

2.0.4 Problem 1D) Basics of clustering: EM Gaussian

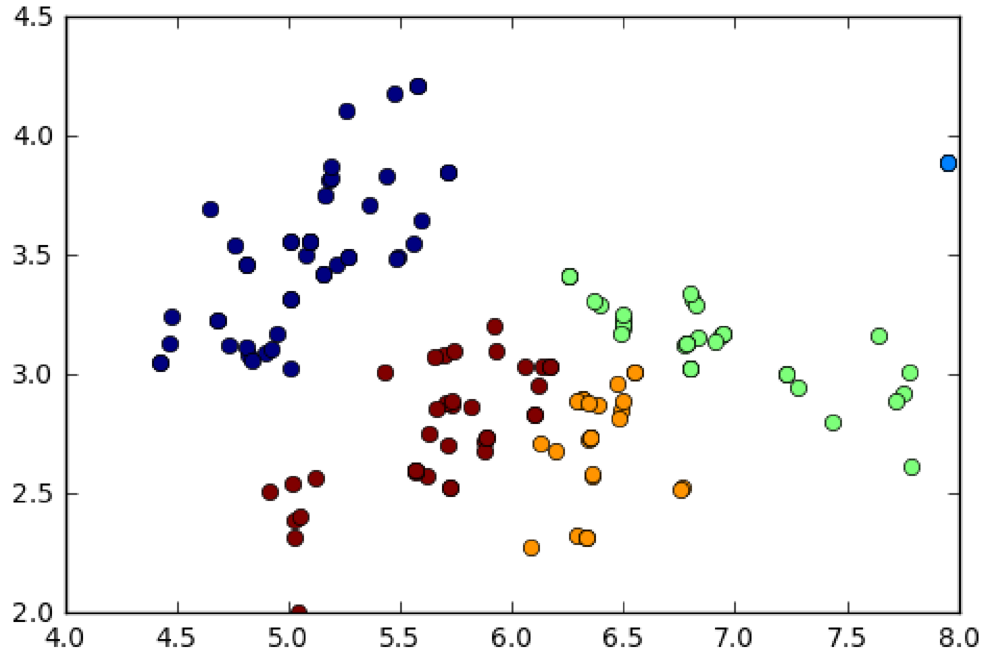
```
In [33]: clusters, parameters, soft, log_likelihood = ml.cluster.gmmEM(X, 5, 'rando

         ml.plotClassify2D(None, X, clusters)

         plt.show()

         print(log_likelihood)


         clusters, parameters, soft, log_likelihood = ml.cluster.gmmEM(X, 5, 'farth

         ml.plotClassify2D(None, X, clusters)

         plt.show()

         print(log_likelihood)
```

```
clusters, parameters, soft, log_likelihood = ml.cluster.gmmEM(X, 5, 'k++')

ml.plotClassify2D(None, X, clusters)

plt.show()

print(log_likelihood)
```

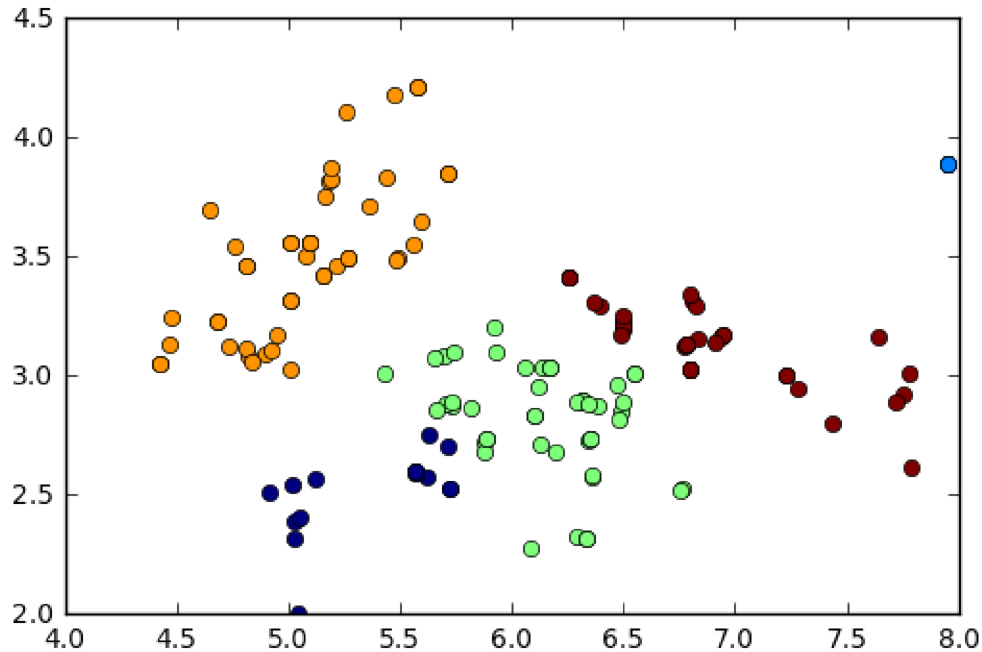



```
-150.288090353
```

```
C:\Python35\CS178\Lab5\mltools\cluster.py:118: VisibleDeprecationWarning: using a r
  clusters[0,:] = X[np.floor(np.random.rand() * m),:]                           # take
```




```
-111.411962017
```



```
-113.196291244
```

2.0.5 Problem 2A) Eigenfaces: zero-mean of face images

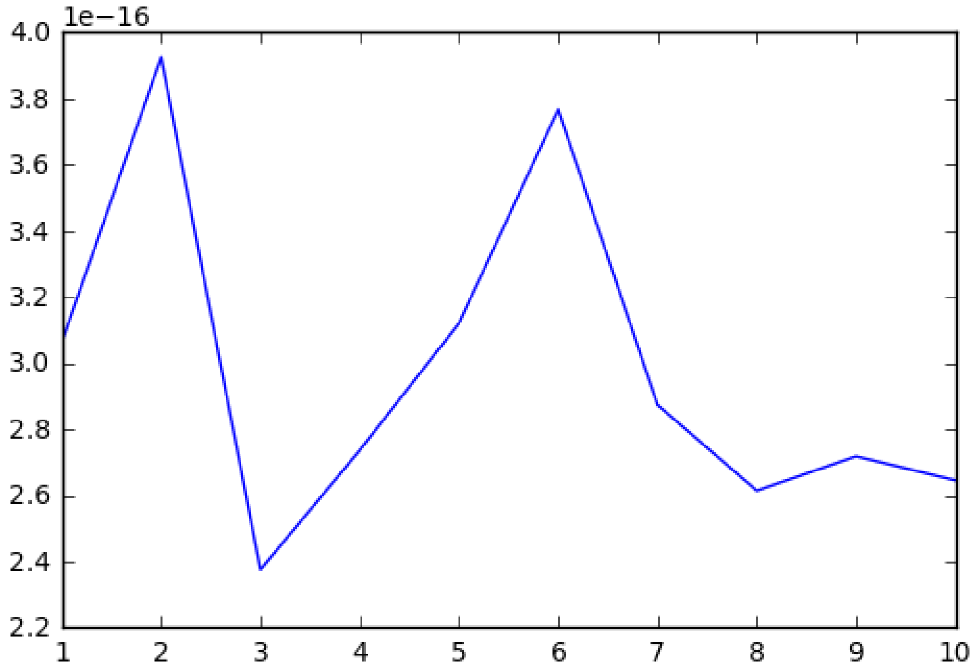
```
In [62]: X = np.genfromtxt("data/faces.txt", delimiter = None)

         # plt.figure()

         # img = np.reshape(X[i,:], (24,24))

         # plt.imshow( img.T, cmap="gray")

         # plt.show()

         # Subtract the mean of the face images from each picture
         XZero = X - np.mean(X,axis = 0)
```

2.0.6 Problem 2B) Eigenfaces: SVD of data

```
In [63]: from scipy import linalg

         # Singlar Value Decomposition
         # decompose a matrix into Unitary left vectors, Singluar values diagonal,
         U, S, Vh = linalg.svd(XZero, full_matrices = False)

         # XZero = W * Vh
         W = U.dot(np.diag(S))
```

2.0.7 Problem 2C) Eigenfaces: MSE values

```
In [58]: K = [1,2,3,4,5,6,7,8,9,10]

         MSE = []

         for k in K:
             #find first k eigendirections
             XzeroHat = W[:,:k].dot(Vh[:k,:])

             MSE.append(np.mean((XZero - XzeroHat)*2))

         plt.plot(K, MSE)

         plt.show()
```

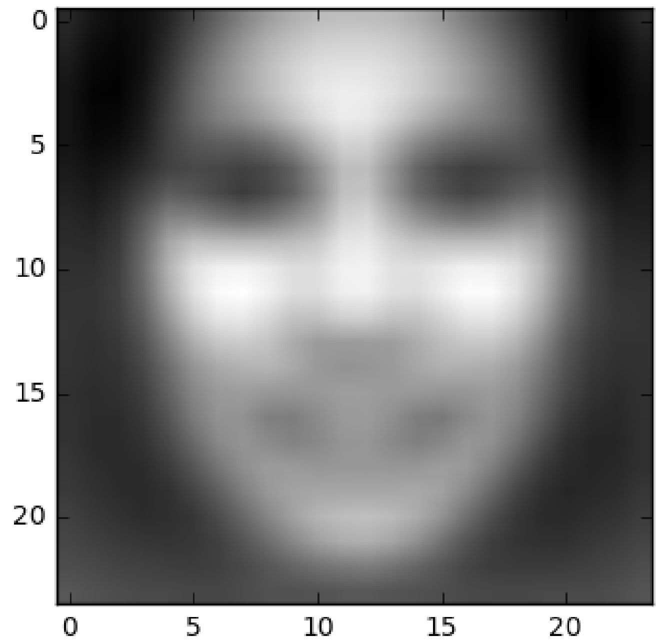


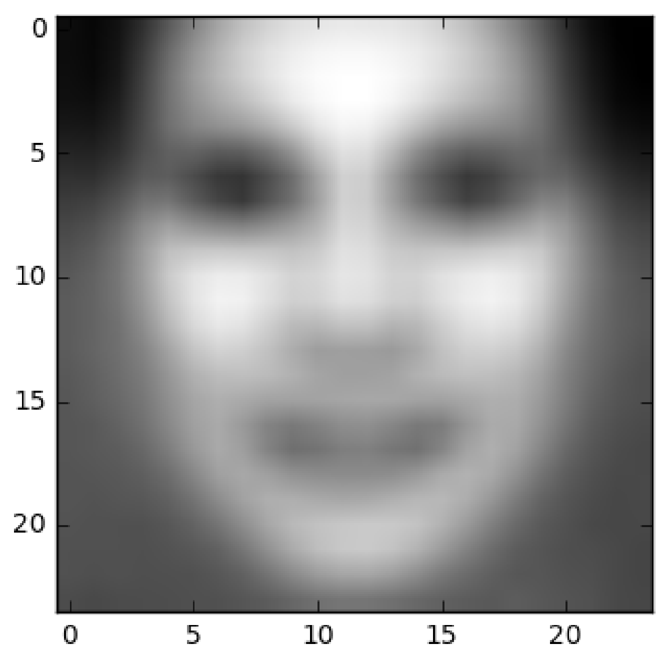
2.0.8 Problem 2D) Eigenfaces: First 3 principal directions

In [85]:
```
# mu + alpha V[i,:]
# mu - alpha V[i,:]

mu = np.mean(X,axis = 0)

for j in range(0,3):

    print("Principal direction #{}".format(j+1))

    alpha = 2 * np.median( np.abs(W[:,j]))

    image1 = np.reshape(mu + alpha * Vh[j,:], (24,24))

    image2 = np.reshape(mu - alpha * Vh[j,:], (24,24))

    plt.figure()

    plt.imshow( image1.T, cmap="gray")

    plt.show()

    plt.imshow( image2.T, cmap="gray")
```

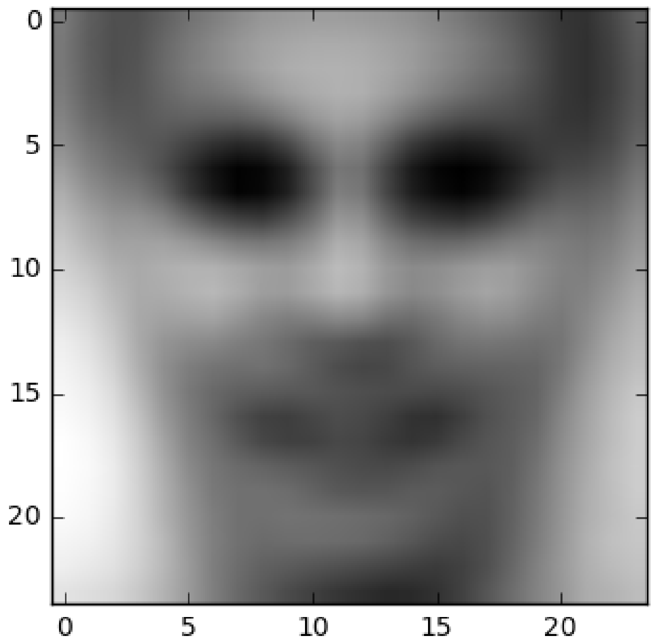
```
    plt.show()
```

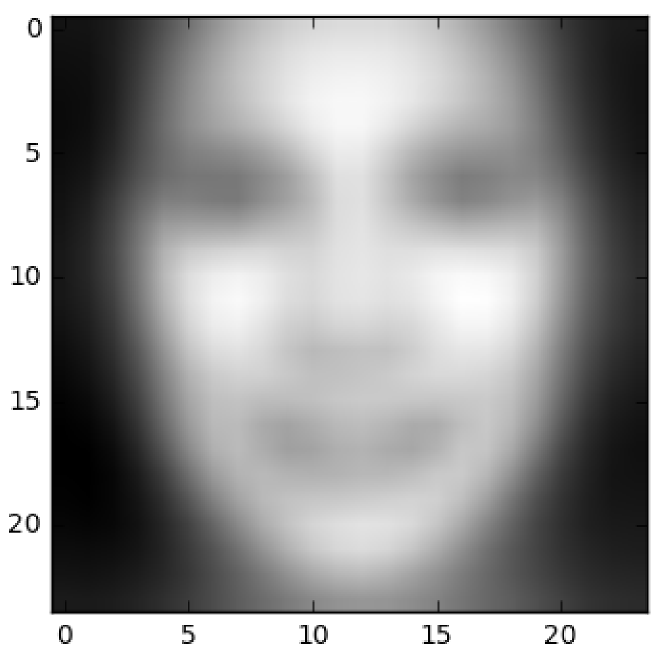
Principal direction #1



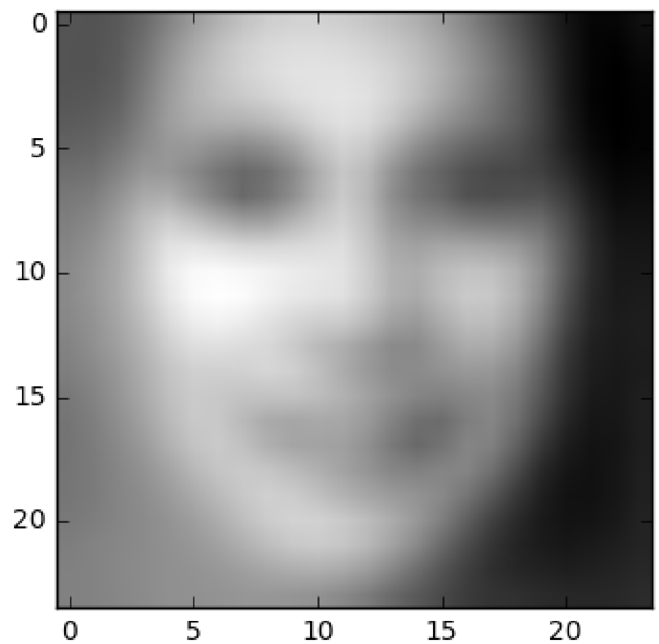


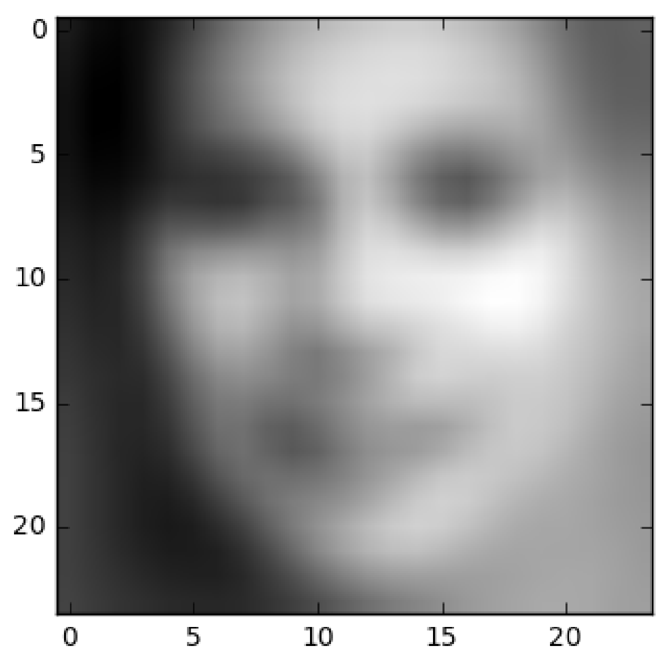
Principal direction #2





Principal direction #3

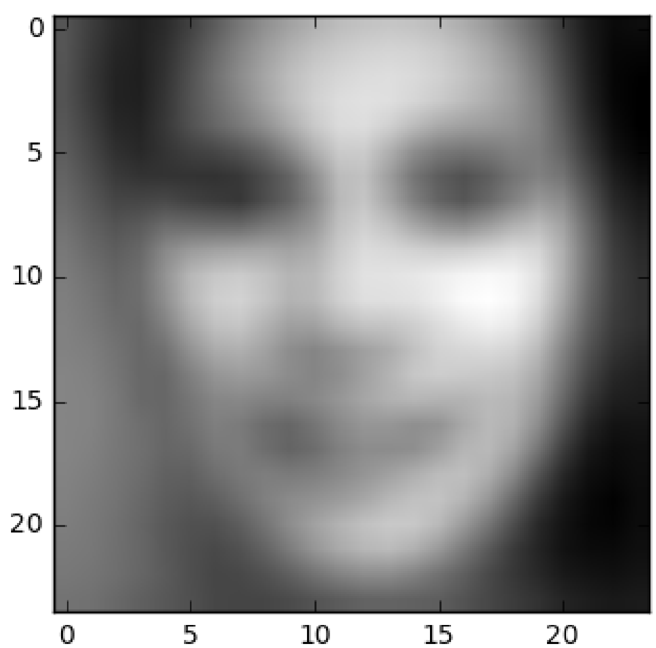


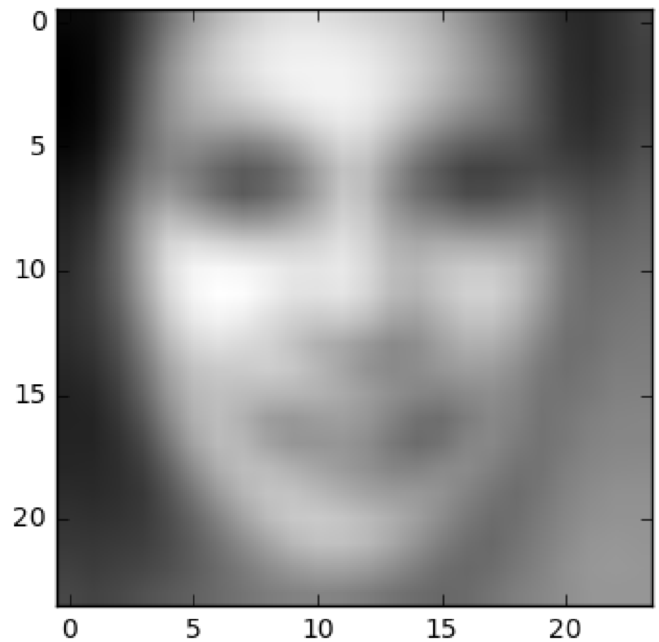


2.0.9 Problem 2E) Eigenfaces: K principal directions

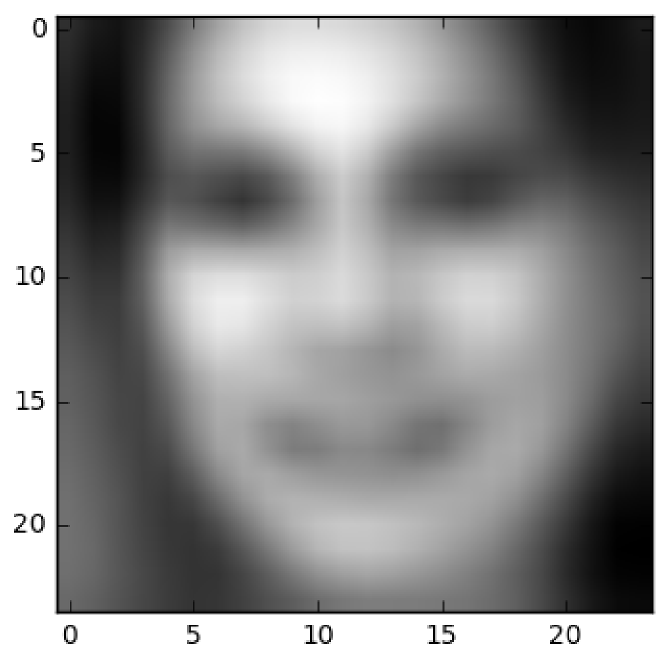
```
In [87]: K = [5,10,50,100]

         for k in K:

             print("Principal direction #{}".format(k))

             alpha = 2 * np.median( np.abs(W[:,k]))

             image1 = np.reshape(mu + alpha * Vh[k,:], (24,24))

             image2 = np.reshape(mu - alpha * Vh[k,:], (24,24))

             plt.figure()

             plt.imshow( image1.T, cmap="gray")

             plt.show()

             plt.imshow( image2.T, cmap="gray")

             plt.show()
```

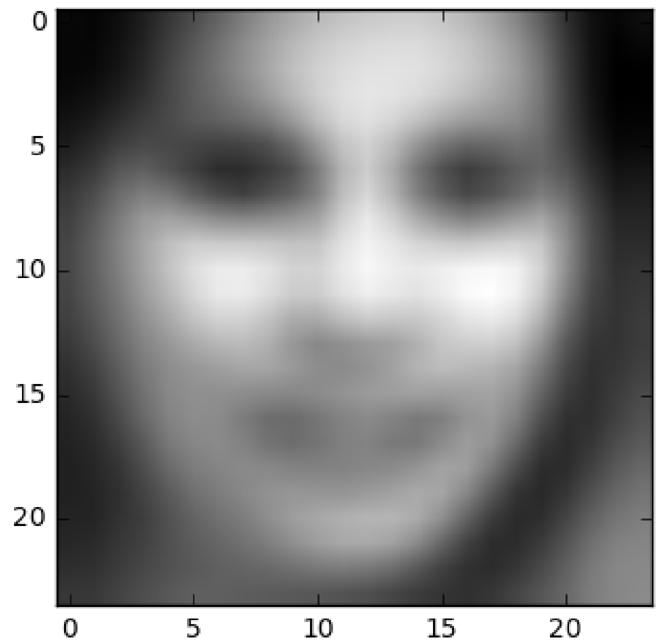
```
Principal direction #5
```



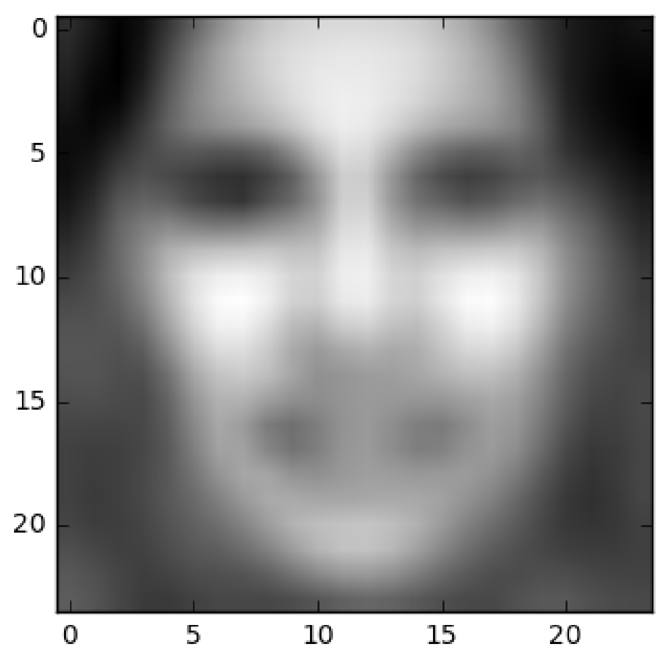


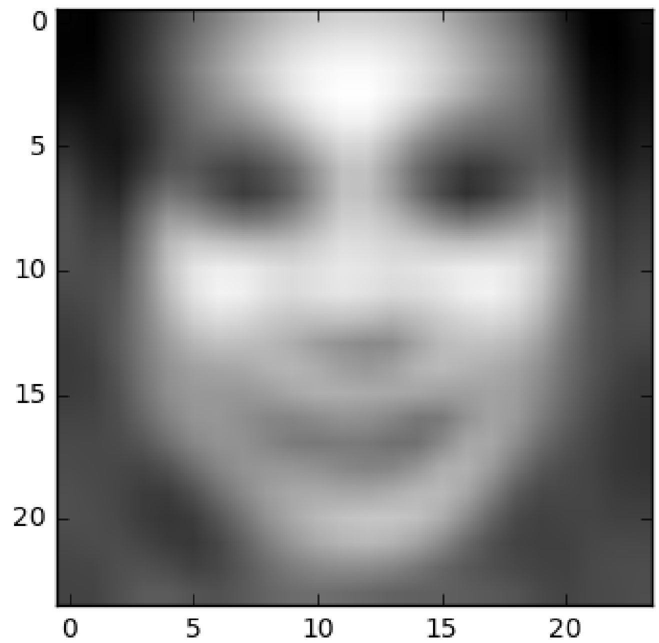
Principal direction #10



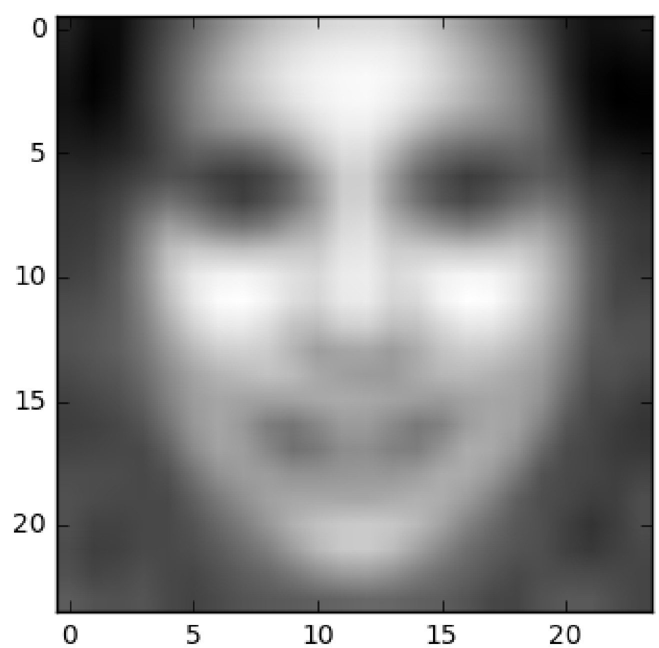


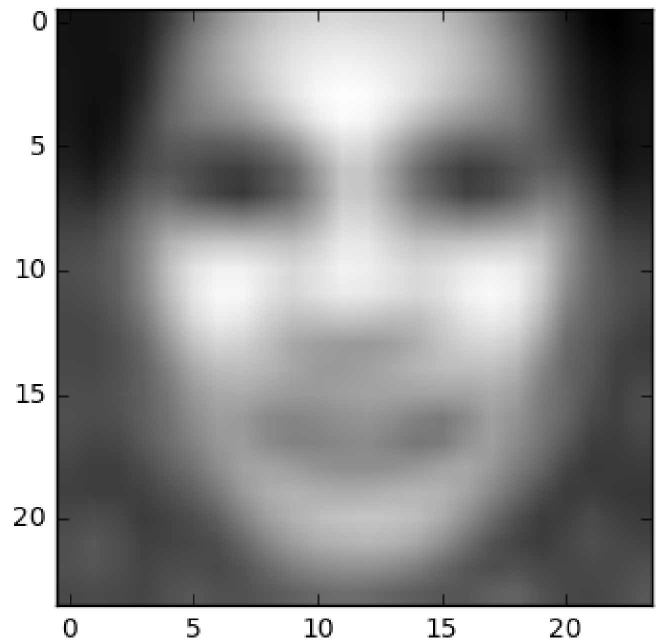
Principal direction #50






```
Principal direction #100
```





2.0.10 Problem 2F) Eigenfaces: PCA latent space methods

In [96]:
```
# first 25 faces
index = list(range(0,25))

# normalize scale of "W" locations
coordinates, parameters = ml.transforms.rescale( W[:,0:2])

plt.figure()

plt.hold(True)

for i in index:

    # compute location of coordinates
    location = (coordinates[i,0], coordinates[i,0] + 0.5, coordinates[i,1]

    img = np.reshape( X[i,:], (24,24))

    plt.imshow( img.T, cmap = "gray", extent = location )

    plt.axis( (-2,3, -2,3) )
```

```
plt.show()
```