CS 178 HW 5

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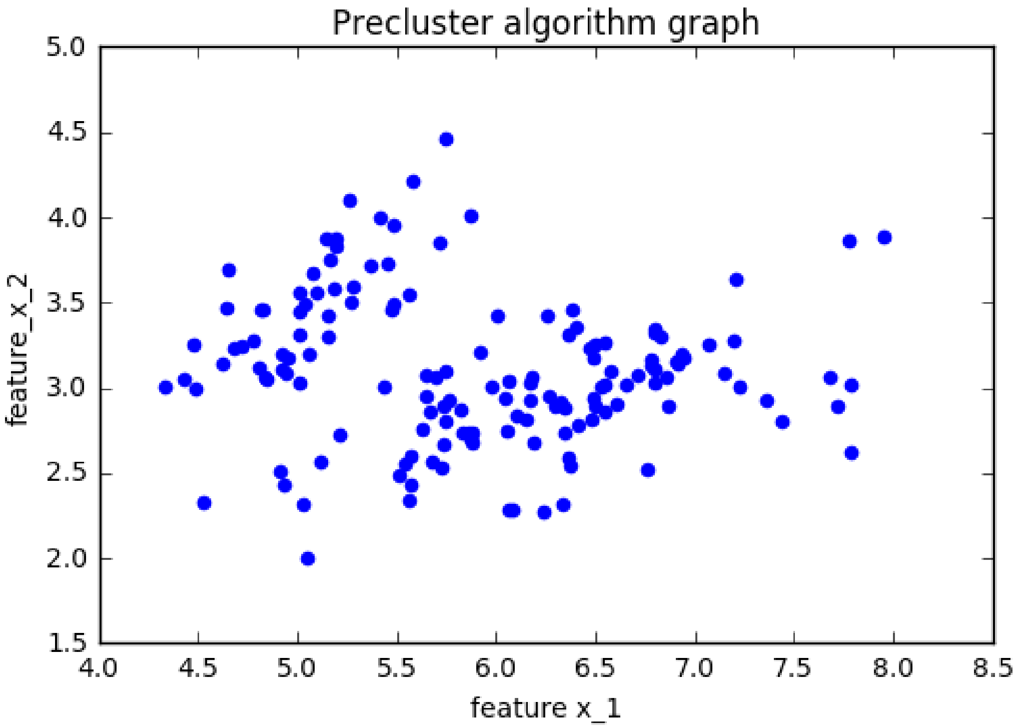
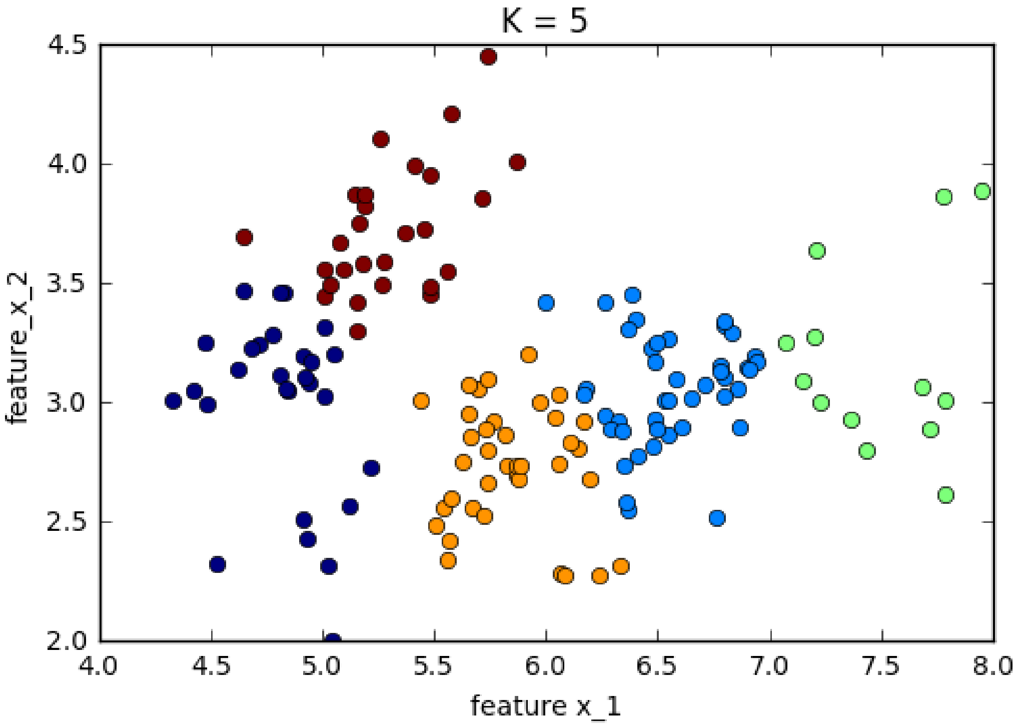
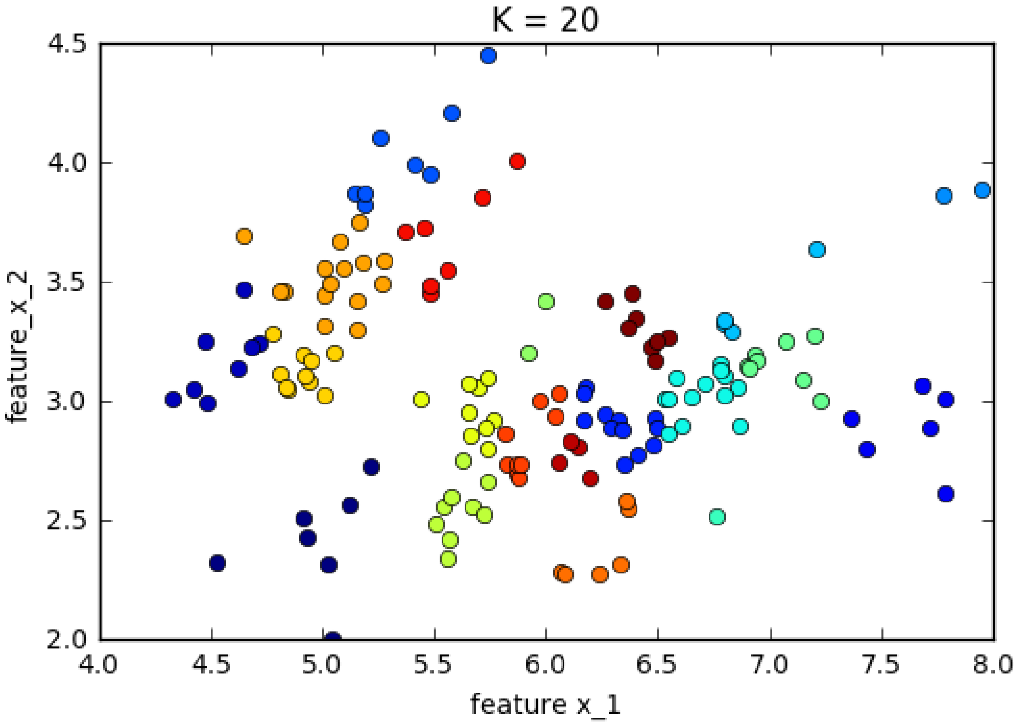
1.1 Problem 1: Basics of Clustering

```
In [2]: import numpy as np
        import matplotlib.pyplot as plt
        import mltools as ml
        import scipy.linalg

        iris = np.genfromtxt('data/iris.txt', delimiter=None)

        X, Y = iris[:,0:2], iris[:,-1]

        # Problem 1: Basics of Clustering

        # 1A
        plt.scatter(X[:,0],X[:,1],color='b')
        plt.xlabel('feature x_1')
        plt.ylabel('feature_x_2')
        plt.title('Precluster algorithm graph')
        plt.show()
```

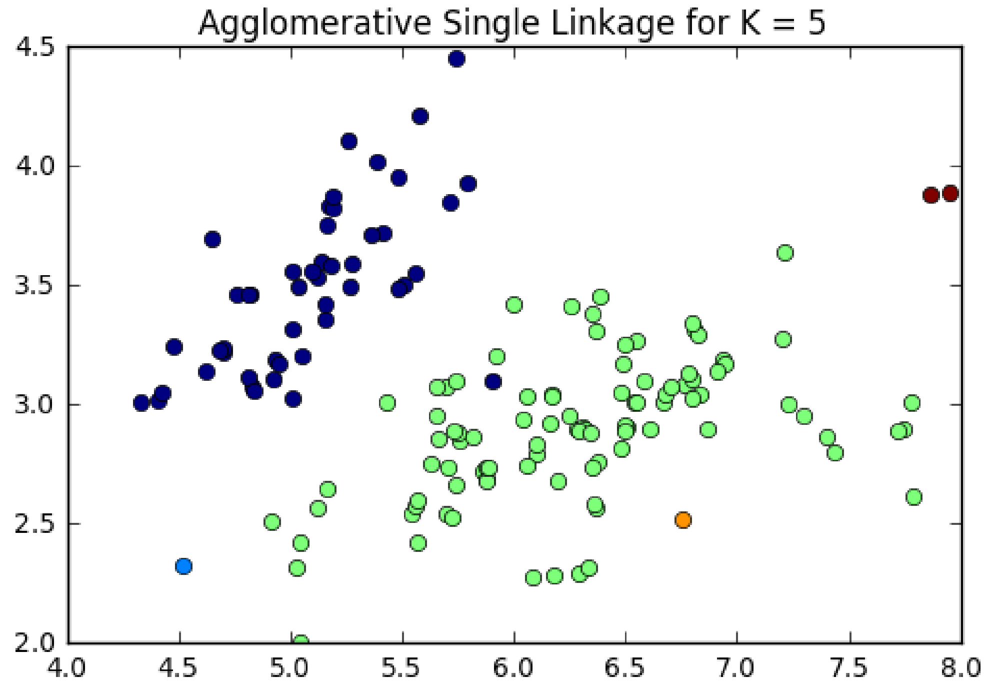


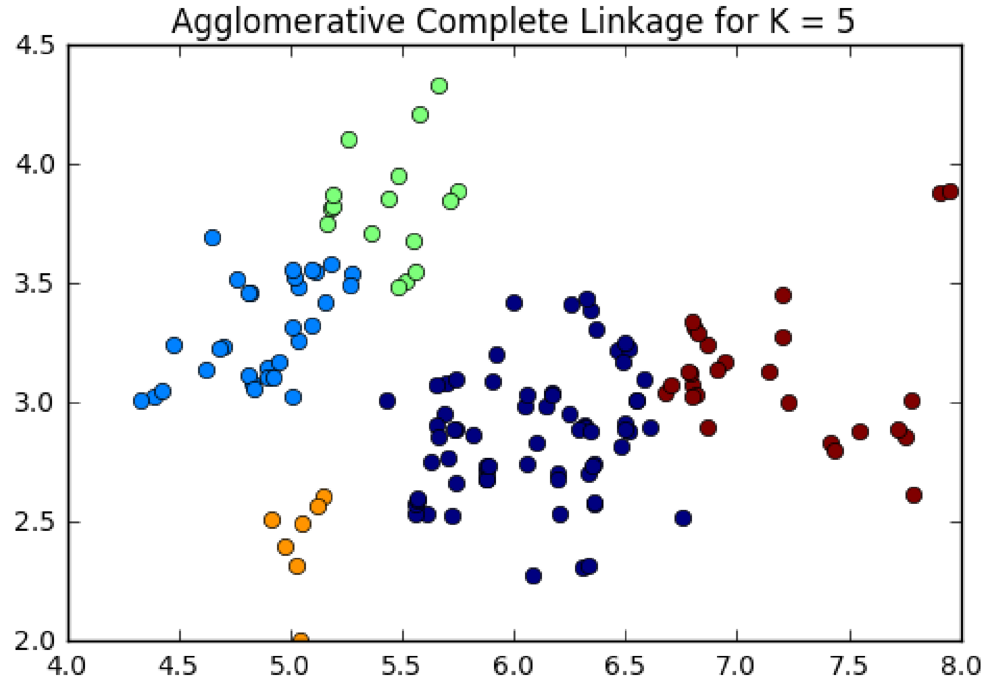
```
In [3]: # 1B

        z,c,d = ml.cluster.kmeans(X,5)
        ml.plotClassify2D(None, X, z)
        plt.title('K = 5')
        plt.xlabel('feature x_1')
        plt.ylabel('feature_x_2')
        plt.show()

        z,c,d = ml.cluster.kmeans(X,20)
        ml.plotClassify2D(None, X, z)
        plt.title('K = 20')
        plt.xlabel('feature x_1')
        plt.ylabel('feature_x_2')
        plt.show()
```

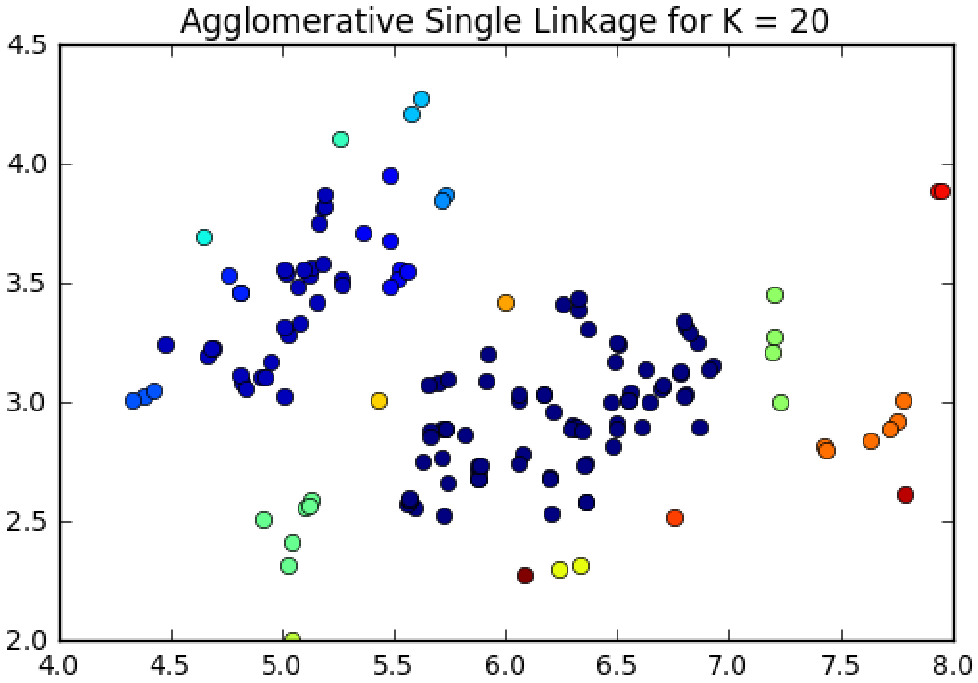

K = 5
4.5
4.0
3.5
3.0
2.5
2.0
feature_x_2
4.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
feature x_1


K = 20
4.5
4.0
3.5
3.0
2.5
2.0
feature_x_2
4.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
feature x_1

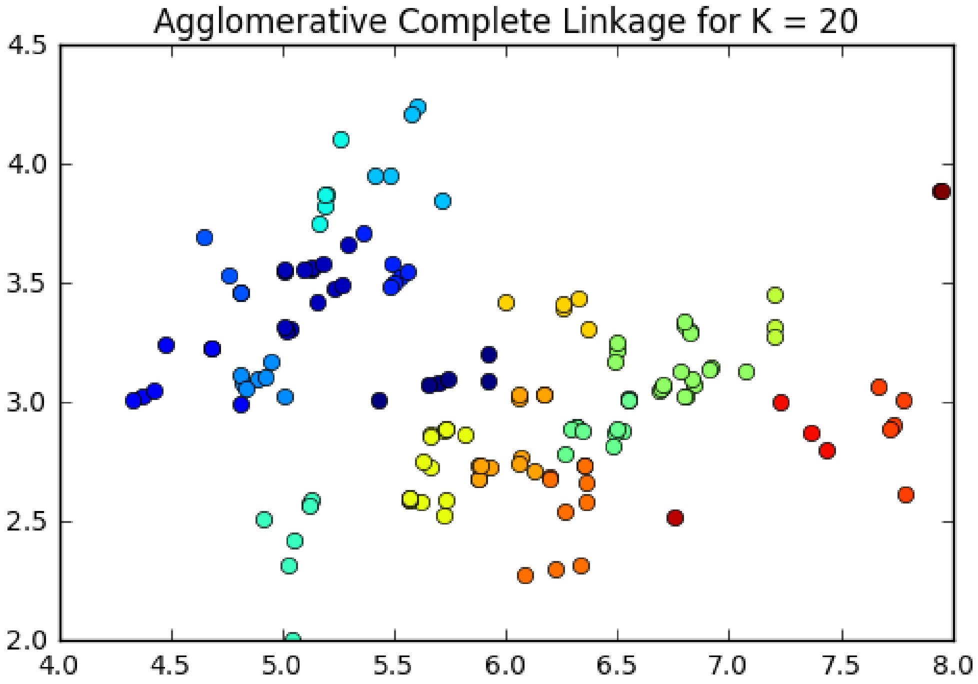
```
In [4]: # 1C

        z, c = ml.cluster.agglomerative(X, 5, method='min')
        plt.title("Agglomerative Single Linkage for K = 5");
        ml.plotClassify2D(None, X, z);
        plt.show()

        z, c = ml.cluster.agglomerative(X, 5, method='max')
        plt.title("Agglomerative Complete Linkage for K = 5");
        ml.plotClassify2D(None, X, z);
        plt.show()

        z, c = ml.cluster.agglomerative(X, 20, method='min')
        plt.title("Agglomerative Single Linkage for K = 20");
        ml.plotClassify2D(None, X, z);
        plt.show()

        z, c = ml.cluster.agglomerative(X, 20, method='max')
        plt.title("Agglomerative Complete Linkage for K = 20");
        ml.plotClassify2D(None, X, z);
        plt.show()

        '''
         The difference between k-means and agglomerative clusters is that
        agglomerative clusters are dendograms. If we use minimum distance
        between clusters it will produce a minimum spanning tree while a
        maximum distance will avoid elongated clusters. This is shown
        in the single and complete linkage for each as single linkage has
        a few clusters that take up the majority while the rest are small or
        single nodes. K-means base each cluster on a center point. The
        initialization of each center may change how the clusters look.
        Distance based or random.
        '''
```


Agglomerative Single Linkage for K = 5
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


Agglomerative Complete Linkage for K = 5
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



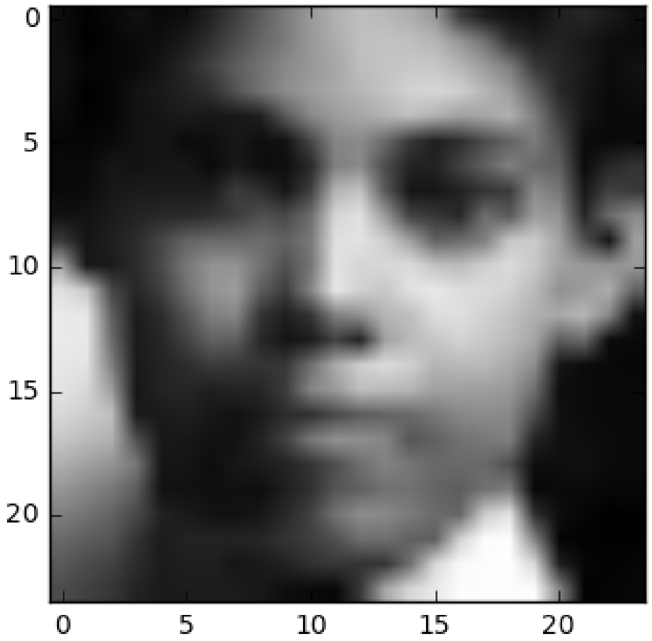
Agglomerative Single Linkage for K = 20



Agglomerative Complete Linkage for K = 20

1.2 Problem 2: Eigenfaces

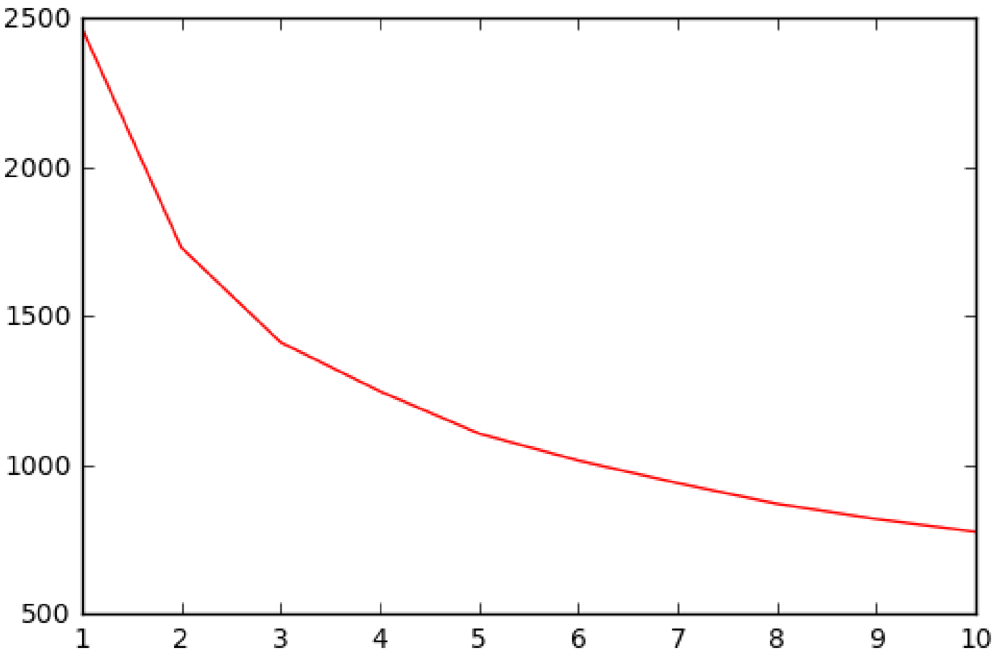
```
In [5]: # Problem 2: Eigenfaces
        X = np.genfromtxt("data/faces.txt", delimiter=None) # load face dataset
        plt.figure()
        # pick a data point i for display
        img = np.reshape(X[5,:],(24,24)) # convert vectorized data point to 24x24 i
        plt.imshow( img.T , cmap="gray") # display image patch; you may have to squ
        plt.show()

        # 2A
        mean = np.mean(X)
        X0 = X-mean

        print("X0 = ",X0)
```



```
('X0 = ', array([[ -23.26595979,  -19.26595979,  -25.26595979, ...,  -37.26595979,
         -102.26595979, -110.26595979],
       [ -97.26595979, -100.26595979,  -97.26595979, ...,  -38.26595979,
          -75.26595979, -113.26595979],
       [-113.26595979, -111.26595979, -110.26595979, ...,  -54.26595979,
          -56.26595979,  -56.26595979],
       ...,
       [ -99.26595979,  -99.26595979, -100.26595979, ...,  -91.26595979,
          -89.26595979,  -84.26595979],
       [ -54.26595979,  -52.26595979,  -51.26595979, ...,  -88.26595979,
          -88.26595979,  -88.26595979],
       [ -62.26595979,  -65.26595979,  -64.26595979, ...,  133.73404021,
          132.73404021,  133.73404021]]))
```

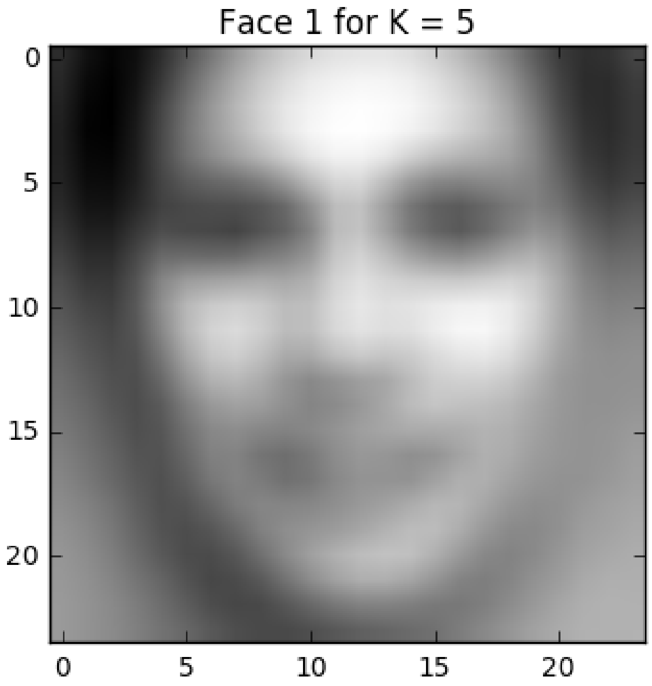
```
In [6]: #2B
        U, S, V = scipy.linalg.svd(X0, full_matrices=False)
        W = U.dot(np.diag(S))
```

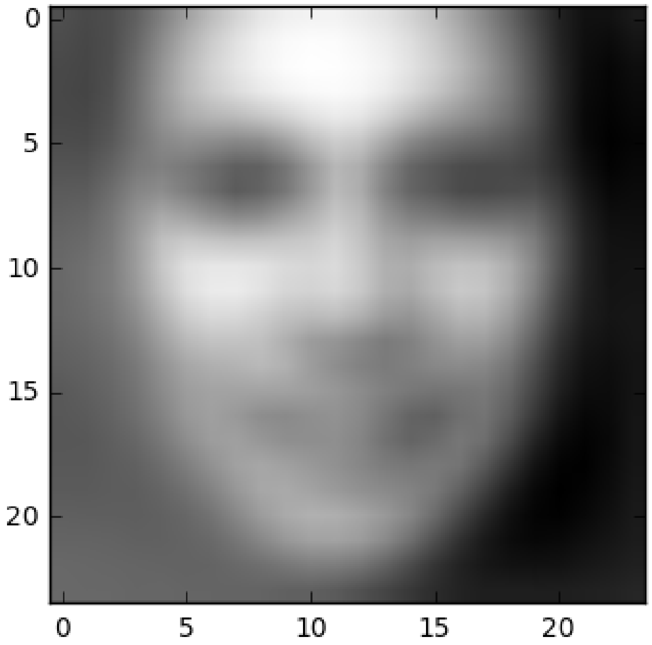
```
In [7]: #2C
        mse = []
        for k in range(1, 11):
            X0hat = W[:, :k].dot(V[:k,:])
            mse.append(np.mean((X0 - X0hat)**2))
        # plot the data
        _, axis = plt.subplots()
        axis.plot(range(1,11), mse, c='red')
        axis.set_xticks(range(1,11))
        plt.show()
```

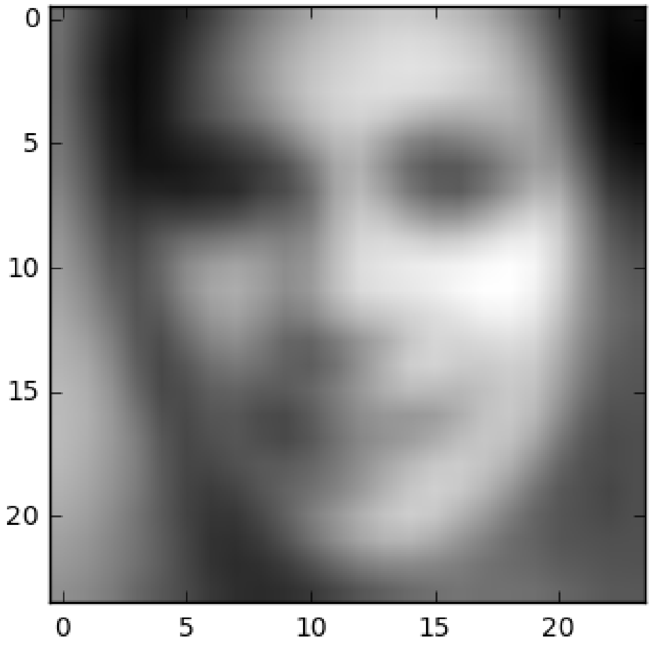


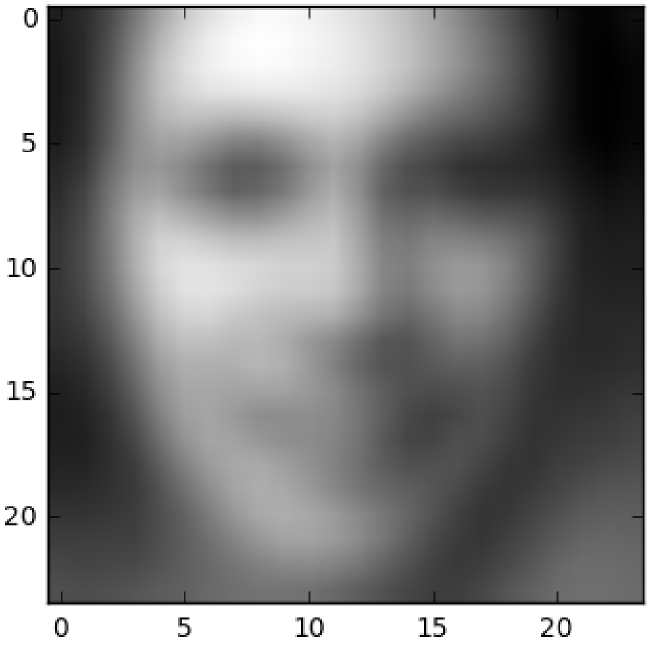
```
In [8]: #2D and 2E
        K = [5,10,50,100]
        for k in K:
            X0hat = W[:, :k].dot(V[:k,:])
            f1 = X0hat[5,:]
            f2 = X0hat[6,:]
```

```
img = np.reshape(f1,(24,24))
plt.imshow(img.T, cmap="gray")
plt.title("Face 1 for K = " + str(k))
plt.show()
img = np.reshape(f2, (24,24))
plt.imshow(img.T, cmap="gray")
plt.title("Face 2 for K = " + str(k))
plt.show()
```

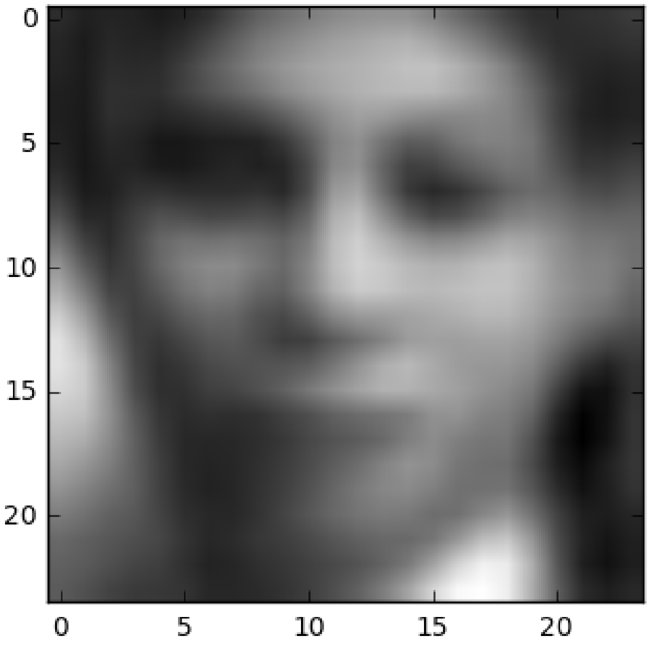



Face 2 for K = 5

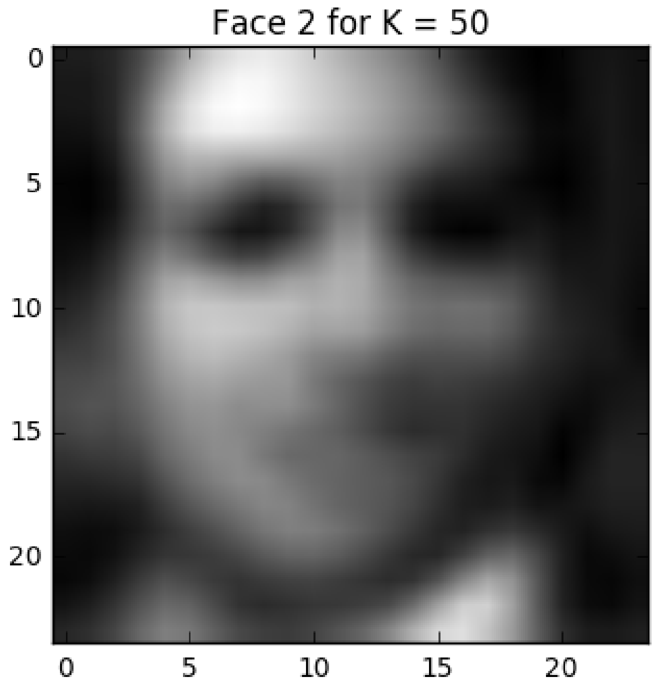

Face 1 for K = 10

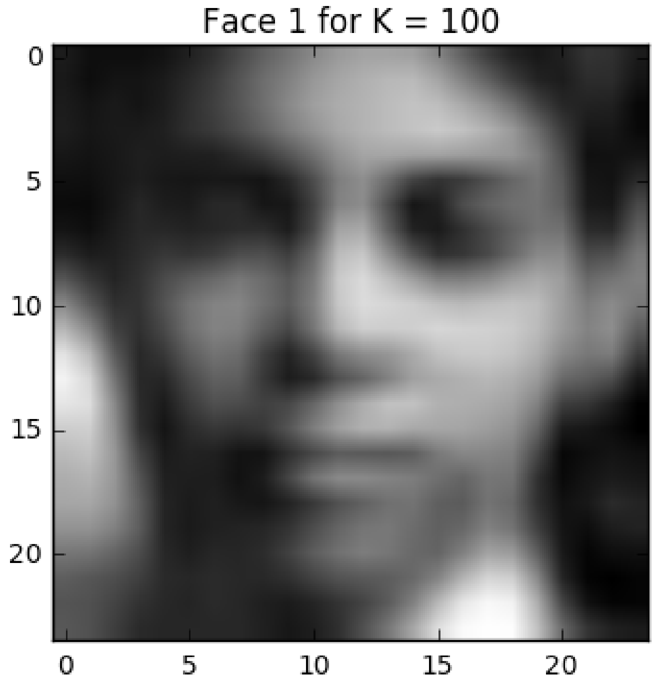


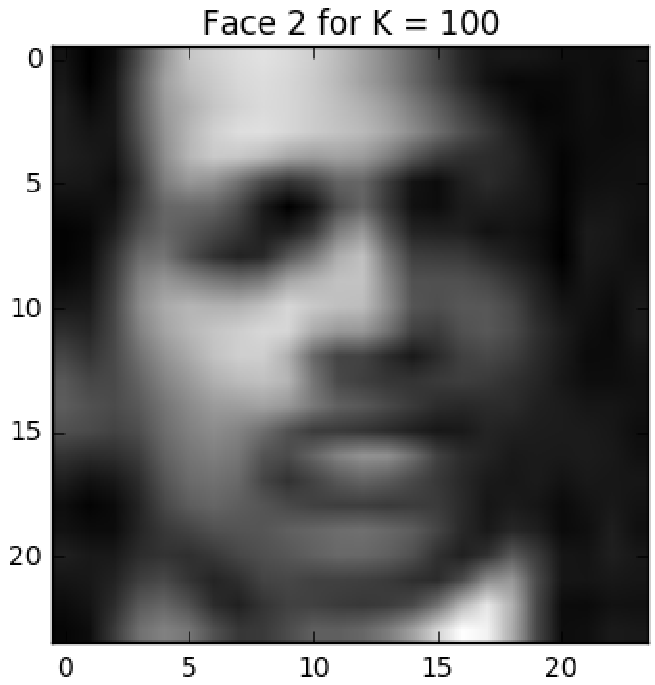
Face 2 for K = 10



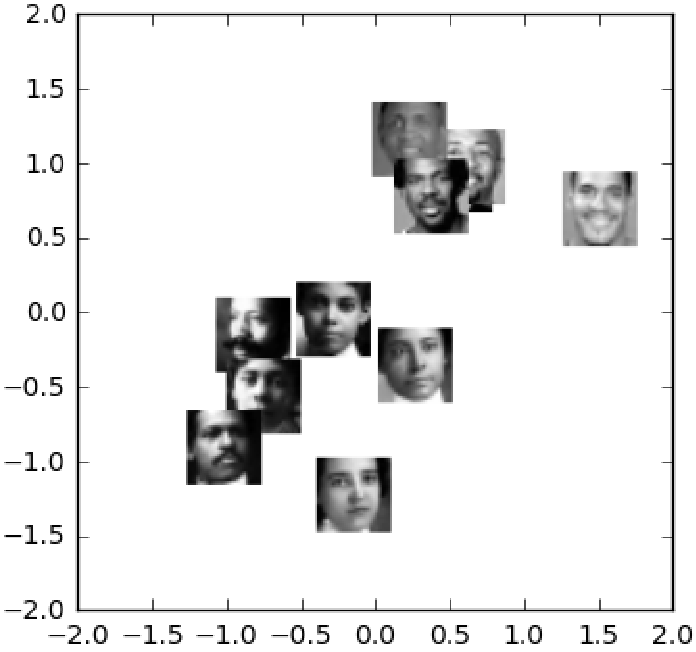
Face 1 for K = 50


Face 2 for K = 50


Face 1 for K = 100



```
In [9]: # Problem 2f
        idx = [0,1,2,3,4,5,6,7,8,9,10]
        coord, params = ml.transforms.rescale(W[:, 0:2])
         # normalize scale of "W" locations
        plt.figure()
        plt.hold(True)
        for i in idx:
            loc = (coord[i,0], coord[i,0] + 0.5, coord[i,1], coord[i, 1] + 0.5)
            # where to place the image & size
            img = np.reshape(X[i,:], (24,24))
            plt.imshow(img.T, cmap="gray", extent=loc) # draw each image
            plt.axis((-2,2,-2,2))
        plt.show()
```


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0