Assignment4_PA_Final

December 10, 2021

Import Libraries

[1]:
```
import numpy as np
import cv2
from os import path
from os import listdir
from os.path import isfile, join
import random
from matplotlib import pyplot as plt
```

[2]:
```
# Define global variables

data_path = 'eigenface_dataset/upload_dataset/';
I = cv2.imread(path.join(data_path,'2b.jpg'),0)
mn = I.shape
m = I.shape[0]
n = I.shape[1]
M = 100 # Number of images in train set
k = np.arange(1,M+1,2) # Number of prinicipal components for (3) & (4)
```

Helper Function to read data the images and generate suitable matrices for furhter processing

[3]:
```
def getData(N):
    '''
    Helper function to generate matrix of N images as
    a matrix of MxN where M is total number of pixels
    in an image
    '''
    data_path = 'eigenface_dataset/upload_dataset/';

    I_size = mn
    MN = I_size[0]*I_size[1]

    # Creating a list of image paths corresponding to 'a' and 'b' category
    # a -> Neurtral
    # b -> Smiling
    image_set_a = [];
    image_set_b = [];
```

```
    onlyfiles = [join(data_path, f) for f in listdir(data_path) if␣
↪isfile(join(data_path, f))]
    sorted(onlyfiles)
    for i in onlyfiles:
        if((i[-5] == 'a') & (i not in image_set_a)):
            image_set_a.append(i)
            i_b = i[0:-5] + 'b' + i[-4:]
            image_set_b.append(i_b)
        elif(i not in image_set_b):
            image_set_b.append(i)
            i_a = i[0:-5] + 'a' + i[-4:]
            image_set_a.append(i_a)

    trainData_a  = np.zeros((MN, N))
    testData_a = np.zeros((MN,171-N))

    trainData_b  = np.zeros((MN, N))
    testData_b = np.zeros((MN,171-N))

    idx_rp = random.sample(range(171), 171)
    img_idx = idx_rp[0:N]
    img_idx_test = idx_rp[N:-1]

    for i in range(len(img_idx)):
        trainData_a[:,i] = cv2.imread(image_set_a[img_idx[i]],0).reshape((MN,))
        trainData_b[:,i] = cv2.imread(image_set_b[img_idx[i]],0).reshape((MN,))
    for i in range(len(img_idx_test)):
        testData_a[:,i] = cv2.imread(image_set_a[img_idx_test[i]],0).
↪reshape((MN,))
        testData_b[:,i] = cv2.imread(image_set_b[img_idx_test[i]],0).
↪reshape((MN,))

    return trainData_a/255, testData_a/255, trainData_b/255, testData_b/255
```

Function to generate the A matrix and mean face.

[4]:
```
def generateDataMatrix(data):
    meanFace = np.mean(data,1,keepdims=True)
    A = data - meanFace
    return meanFace, A
```

[5]:
```
# Prepare dataset by splitting into test and train set
dataTrain_a, dataTest_a, dataTrain_b, dataTest_b = getData(M)
meanFace_a, A_a = generateDataMatrix(dataTrain_a)
meanFace_b, A_b = generateDataMatrix(dataTrain_b)
```

Generate eigen faces

[6]:
```python
def generateEigenFaces(A):
    '''
    Helper function to generate M
    eigenface from normalized face matrix.
    '''
    # Generate L using AT*A
    L = np.matmul(np.transpose(A),A)
    # Calculate eigenvectors and eigenvalues
    [l,e] = np.linalg.eigh(L)
    # sort eigenvectors and eigenvalues based on eigenvalue
    l = np.flip(l)# l[idx]#
    e = np.flip(e,1)# e[:,idx]#
    eigen_faces = np.matmul(A,e)
    # Normalize eigen faces
    eigen_faces = eigen_faces/np.linalg.norm(eigen_faces,2,axis=0)
    return eigen_faces,l
```

Helper function to plot K of the M eigenfaces

[7]:
```python
def plotKEigenFaces(eigen_faces, meanFace, K = 10):
    '''
    Helper function to plot K eigenfaces
    '''
    plt.figure(figsize=(20,20))
    plt.suptitle(str(K) + ' most representative eigen faces')
    eigen_faces = eigen_faces
    for i in range(K):
        ef = eigen_faces[:,i]
        I_ef = ef.reshape((m,n))
        plt.subplot(int(K/2),2,i+1)
        plt.imshow(I_ef, cmap='gray')
        plt.axis('off')
    plt.show()
```

Helper function to plot image

[8]:
```python
def plotImage(I, title):
    '''
    Plot image
    '''
    plt.imshow(I, cmap = 'gray')
    plt.title(title)
    plt.axis('off')
    plt.show()
```

Function reconstructs given image and eigen faces

```python
[9]: def reconstructFace(T,meanFace,eigenfaces):
         '''
         Given a face, project onto face space
         '''
         T_normalized = T - meanFace
         # Get its component along each eigenvector
         w = np.matmul(eigenfaces.T,T_normalized)
         # Revonstruct face
         recon_face_v = np.matmul(eigenfaces,w) + meanFace
         return recon_face_v
```

Calculate MSE

```python
[10]: def calculateMSE(recon_face_v, T):
          '''
          Calculate MSE
          '''
          mse = np.square(T - recon_face_v)
          return np.mean(mse)
```

Run re-construction on given image and eigen faces using differnet number of prinicipal components

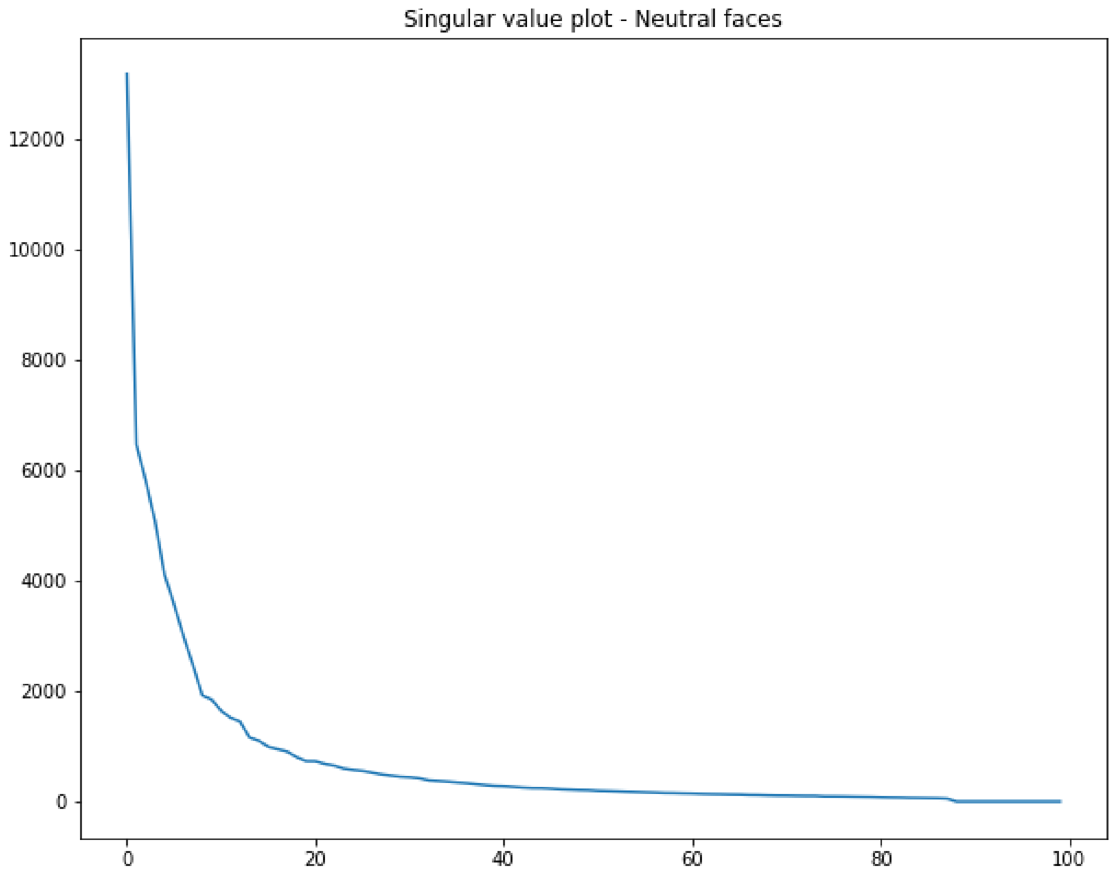
```python
[11]: def runReconExp(T, eigen_faces, meanFace):
          '''
          Sweep across differnet number of prinicipal components.
          Plot each reconstructed eigenface and return MSE
          '''

          MSE_Error = np.zeros_like(k).astype(np.float64)
          plt.figure(figsize=(15,15))
          plt.suptitle('Reconstructed Faces')
          for i in range(k.shape[0]):
              K = k[i]

              recon_face_v = reconstructFace(T, meanFace, eigen_faces[:,np.arange(K)])

              # Calculate MSE
              MSE_Error[i] = calculateMSE(recon_face_v, T)

              recon_face = recon_face_v.reshape((m,n))

              plt.subplot(int(k.shape[0]/5),5,i+1)
              plt.imshow(recon_face, cmap = 'gray')
              plt.title(str(K))
              plt.axis('off')
          plt.show()
          return MSE_Error
```

Plot MSE

[12]:
```
def plotMSE(MSE_Error):
    '''
    Helper function to plot MSE
    '''
    plt.figure(figsize=(10,8))
    ax = plt.plot(MSE_Error)
    t = np.arange(0,k.shape[0]+1,2)
    plt.xticks(t, t*2)
    plt.title('MSE vs # Principal Components')
    plt.xlabel('Number of Prinicipal Components')
    plt.ylabel('Mean Squared Error')
    plt.show()
```

PA (1)
Plot 10 most representative eigen faces of neutral face data-set

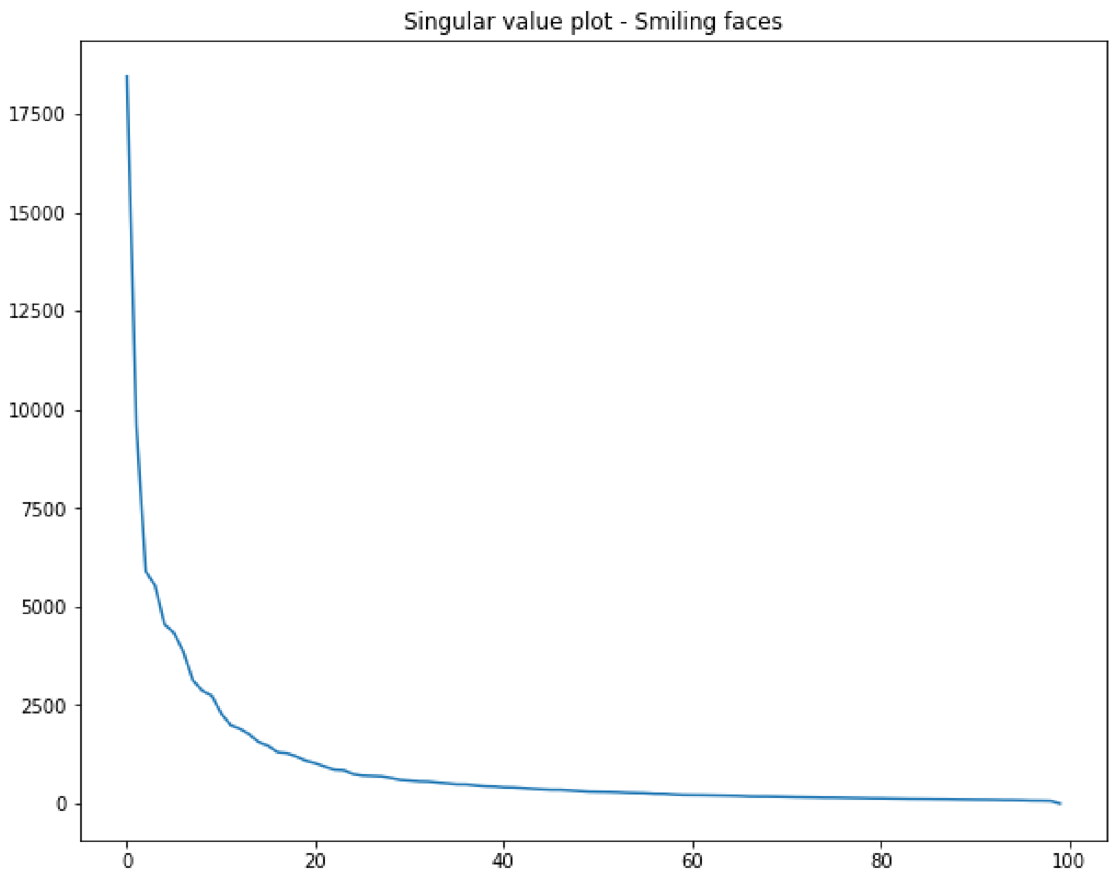
[13]:
```
eigen_faces_a,l = generateEigenFaces(A_a)

plt.figure(figsize=(10,8))
plt.plot(l)
plt.title('Singular value plot - Neutral faces')

plotKEigenFaces(eigen_faces_a, meanFace_a, 10)
```


Singular value plot - Neutral faces
12000
10000
8000
6000
4000
2000
0
0
20
40
60
80
100

10 most representative eigen faces

PA (1)
Plot 10 most representative eigen faces of smiling face data-set

[14]:
```
eigen_faces_b, l = generateEigenFaces(A_b)

plt.figure(figsize=(10,8))
plt.plot(l)
plt.title('Singular value plot - Smiling faces')

plotKEigenFaces(eigen_faces_b, meanFace_b, 10)
```



10 most representative eigen faces

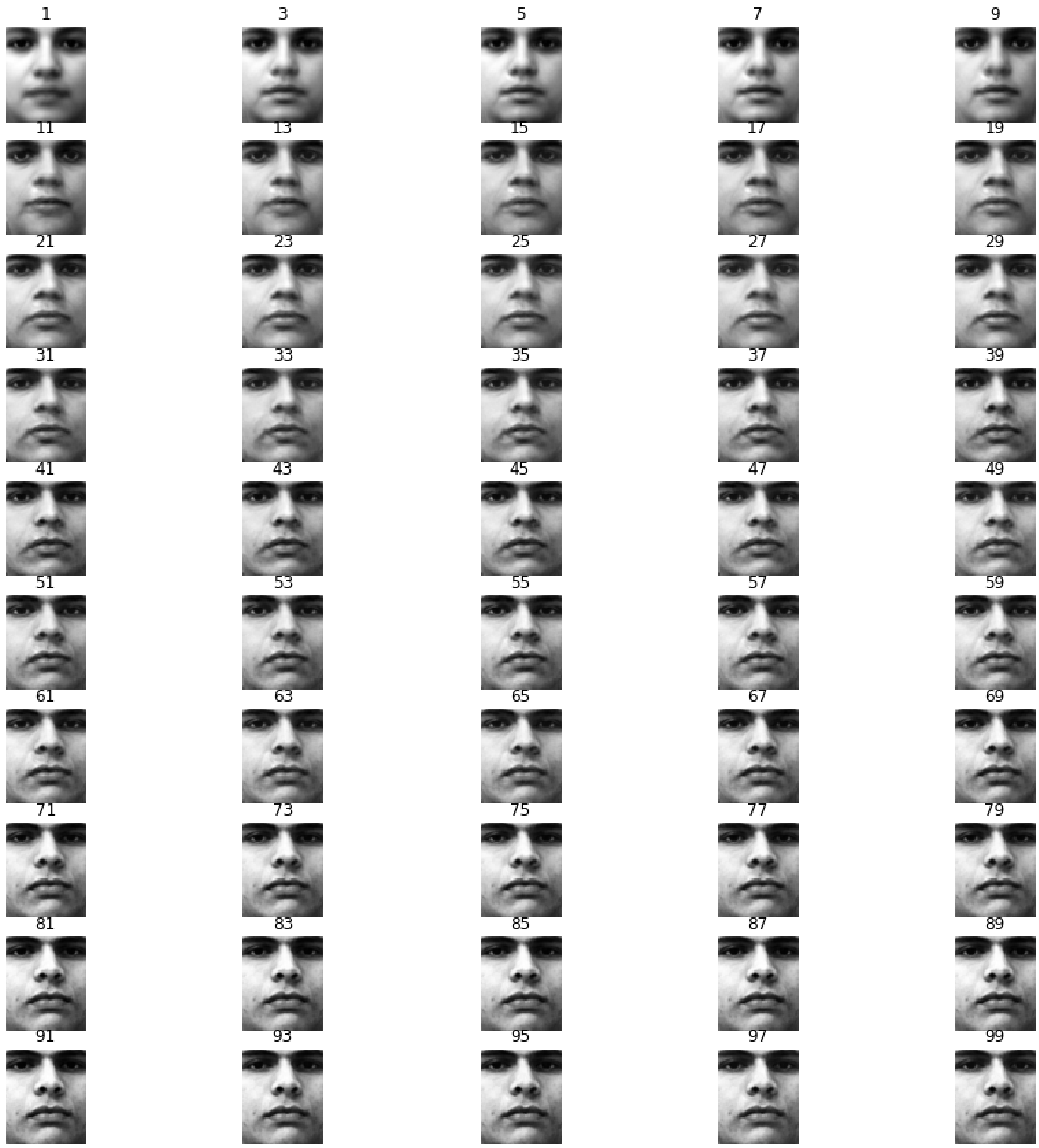
From the plots of singular values above, it is evident that the first 40(approx.) eigen vectos / faces hold the maximum information and are hence sufficient to hold the

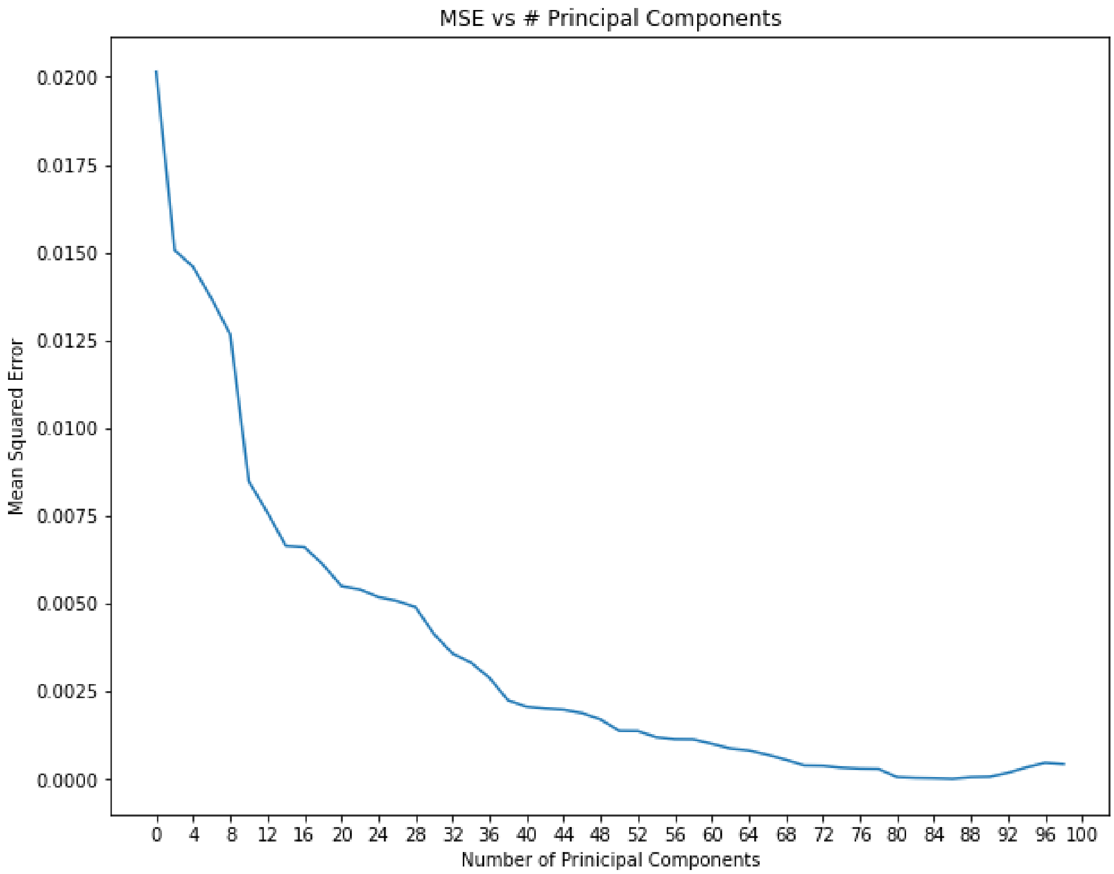
[15]:
```
eigen_faces_a_basis = eigen_faces_a[:,range(100)]
eigen_faces_b_basis = eigen_faces_b[:,range(100)]
```

PA(2)
Reconstruct training image from neutral faces

[16]:
```
# Pick a training Image
T = dataTrain_a[:,[0]]
og_face = T.reshape((m,n))

# Original image
plotImage(og_face, 'Original Image')

# Reconstruct using differnent number of components
MSE_Error = runReconExp(T, eigen_faces_a, meanFace_a)

# Plot Error
plotMSE(MSE_Error)
```

Reconstructed Faces

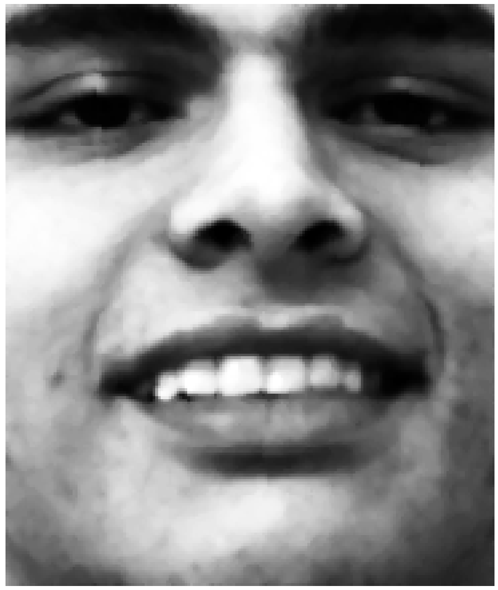


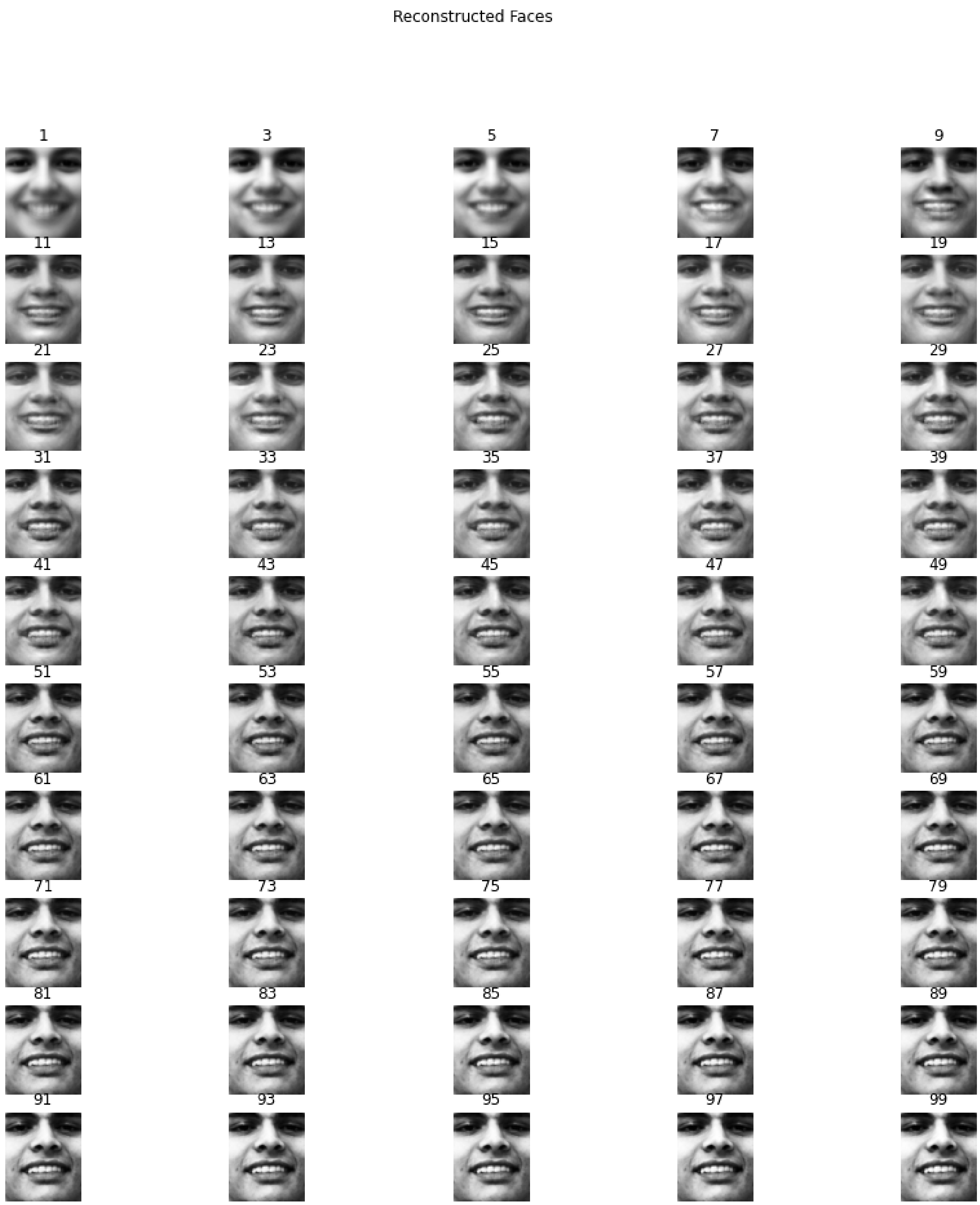


PA(2)
Reconstruct training image from smiling faces

[17]:
```
# Pick a training Image
T = dataTrain_b[:,[0]]
og_face = T.reshape((m,n))

# Original image
plotImage(og_face, 'Original Image')

# Reconstruct using differnent number of components
MSE_Error = runReconExp(T, eigen_faces_b, meanFace_b)

# Plot Error
plotMSE(MSE_Error)
```

Original Image




Reconstructed Faces
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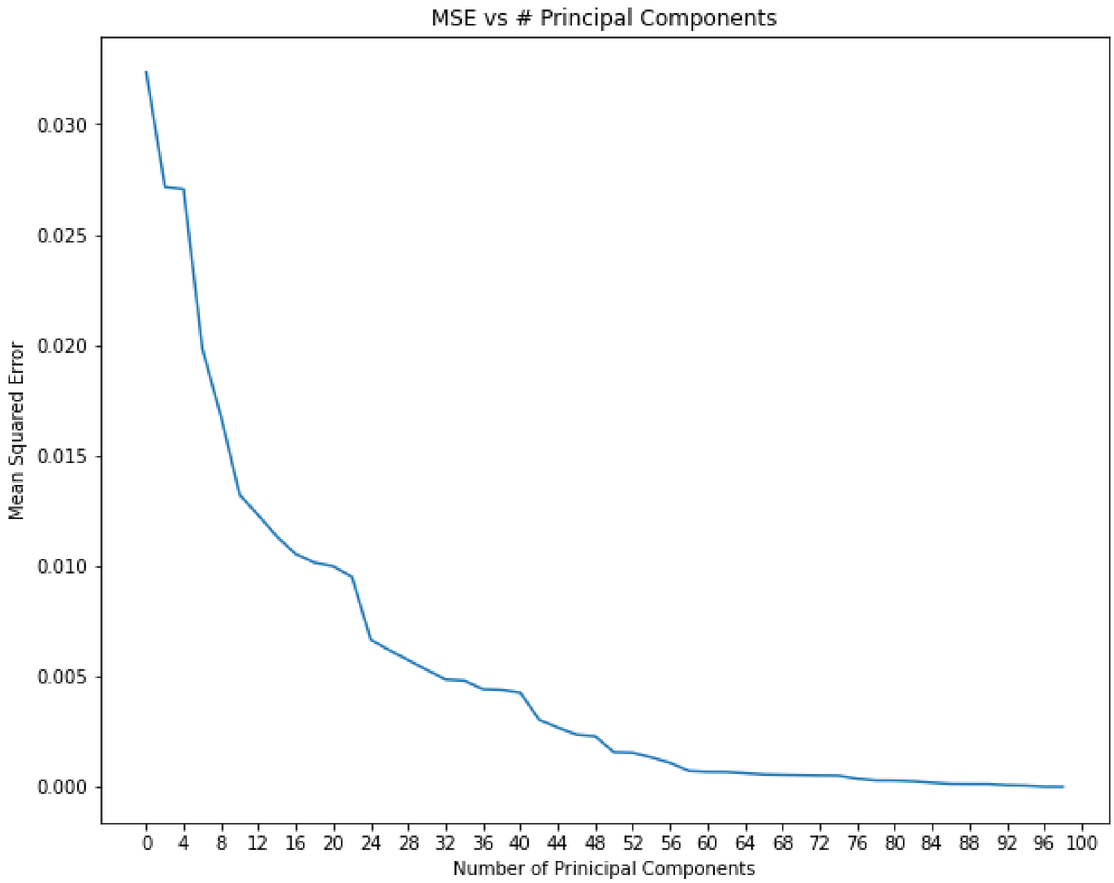


PA(2)
Reconstruct test image from neutral faces

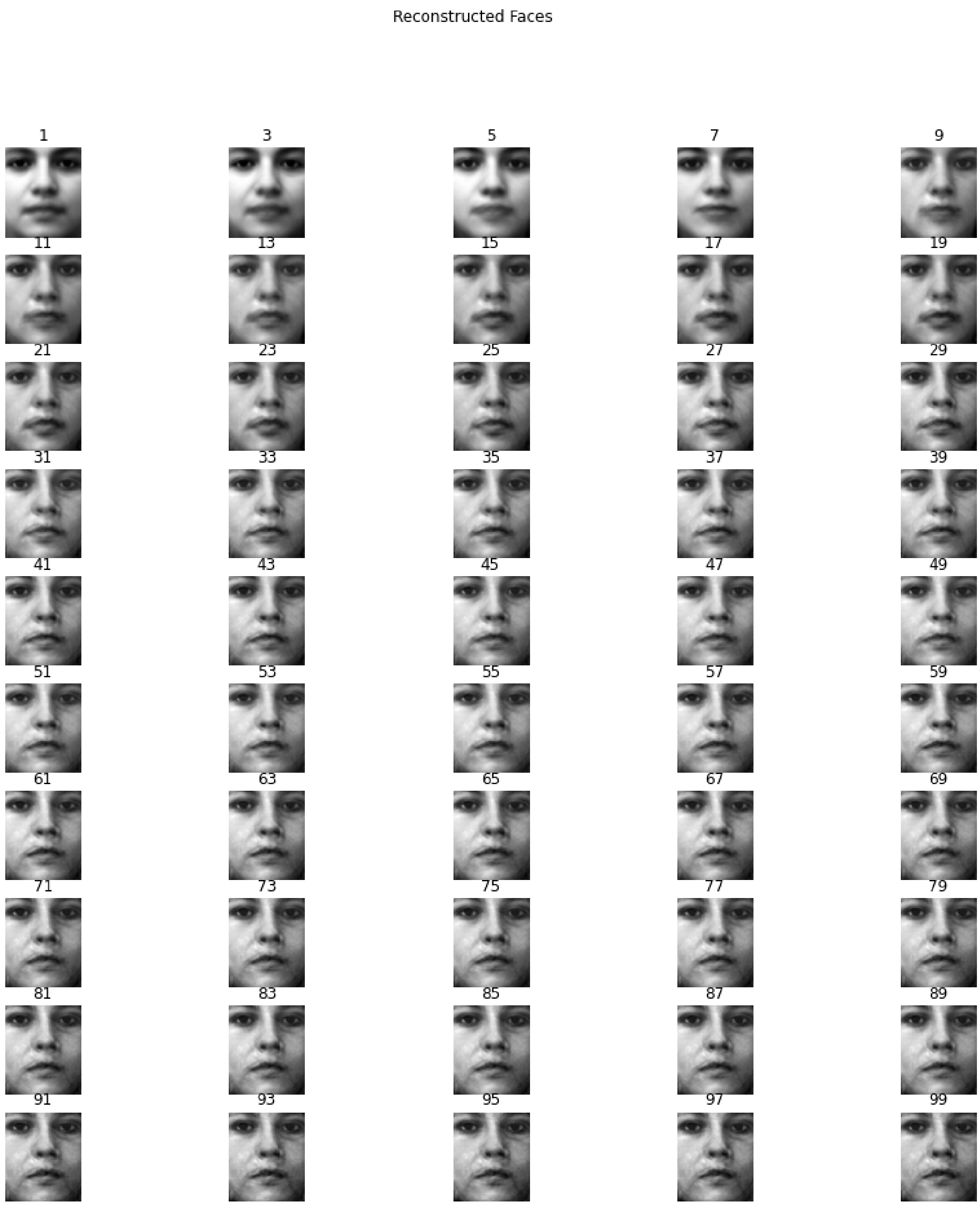
[18]:
```
# Pick a training Image
T = dataTest_a[:,[0]]
og_face = T.reshape((m,n))

# Original image
plotImage(og_face, 'Original Image')

# Reconstruct using differnent number of components
MSE_Error = runReconExp(T, eigen_faces_a, meanFace_a)

# Plot Error
plotMSE(MSE_Error)
```


Original Image


Reconstructed Faces
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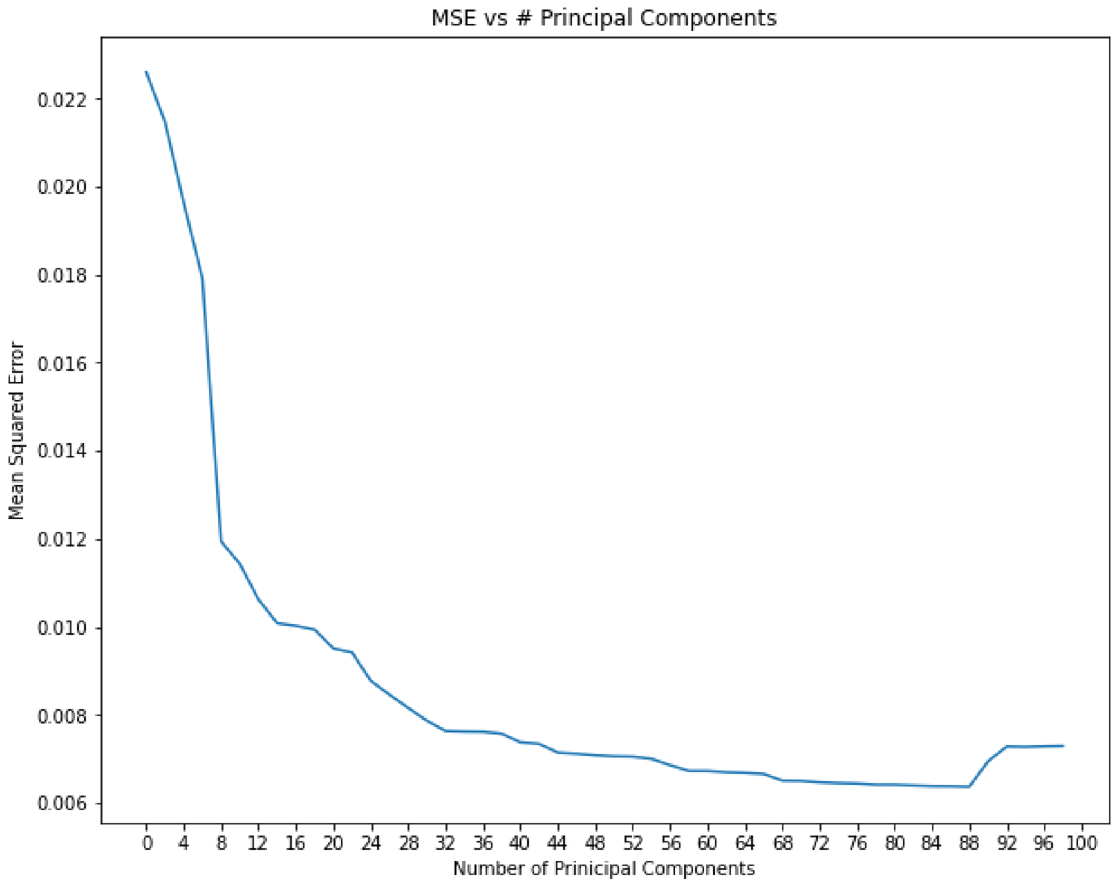
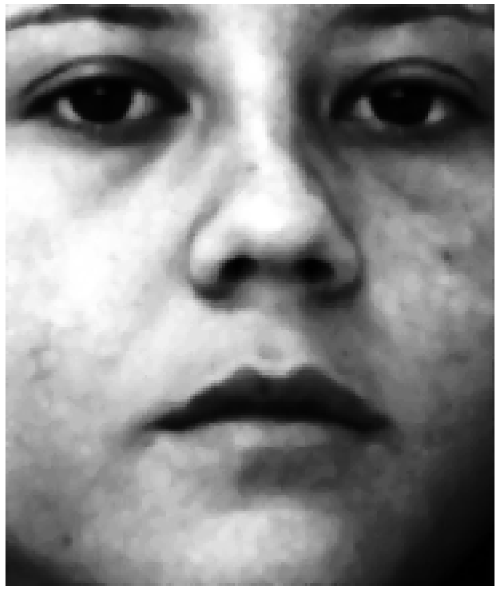
99

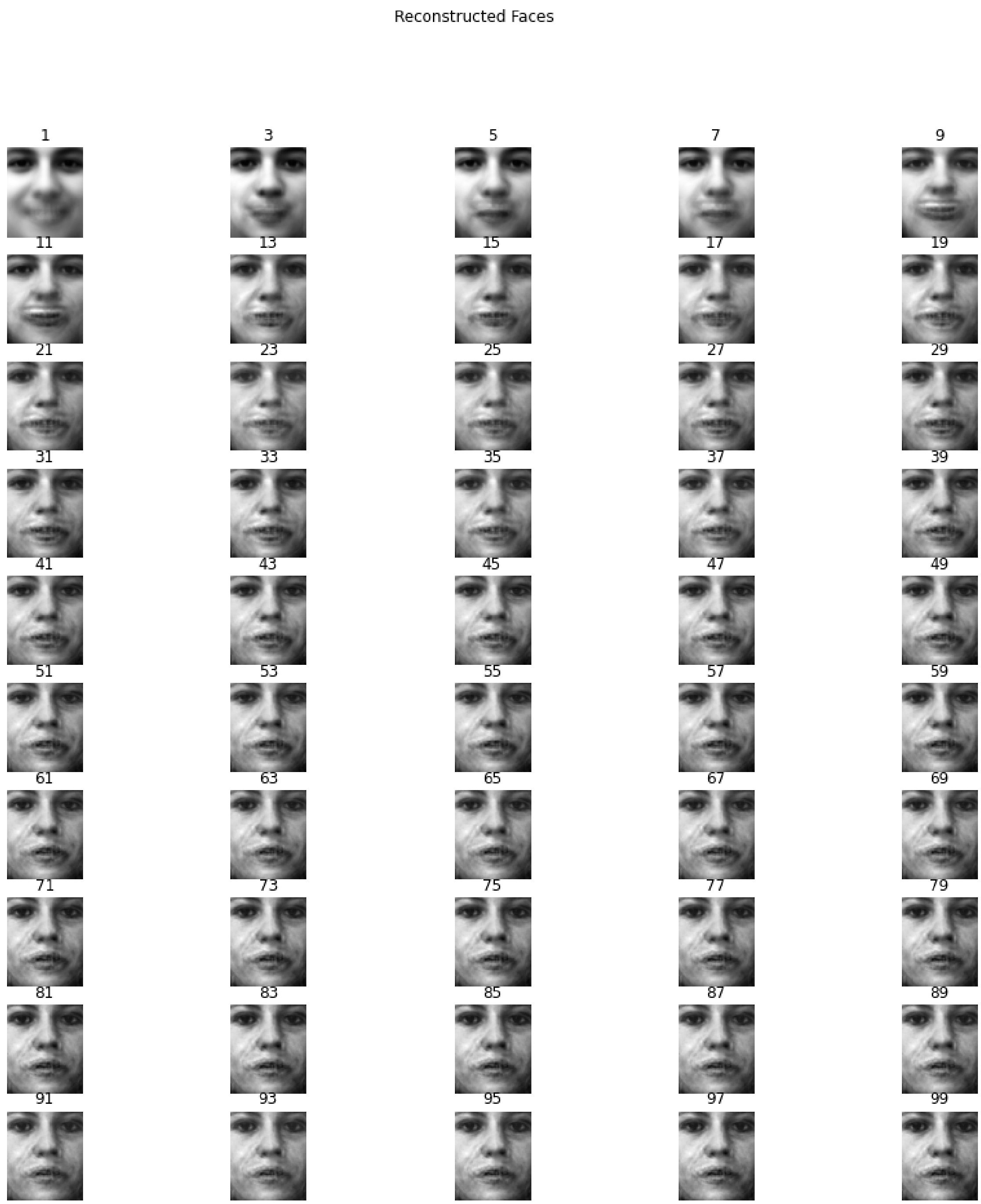


PA(2)
Reconstruct test image from smiling faces

[19]:
```
# Pick a training Image
T = dataTest_b[:,[0]]
og_face = T.reshape((m,n))

# Original image
plotImage(og_face, 'Original Image')

# Reconstruct using differnent number of components
MSE_Error = runReconExp(T, eigen_faces_b, meanFace_b)

# Plot Error
plotMSE(MSE_Error)
```

Original Image




Reconstructed Faces
1
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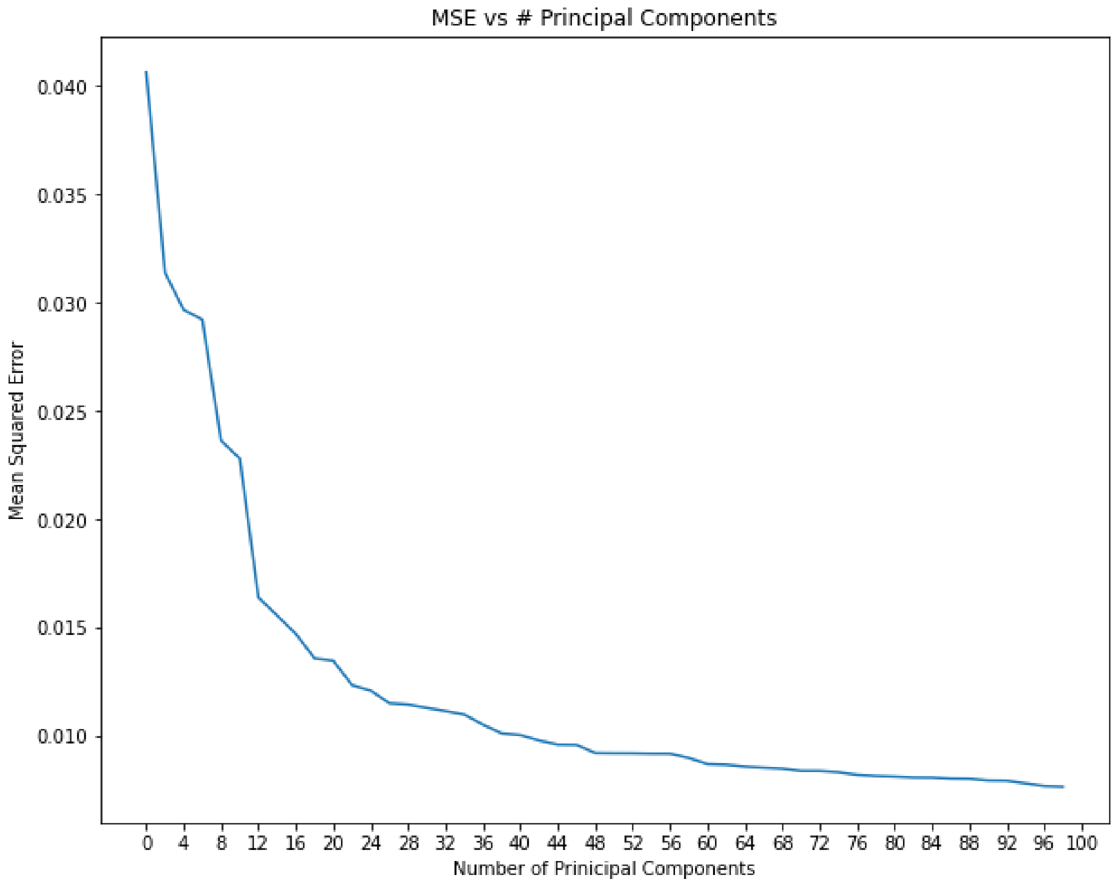

The plots of the reconstruction error with number of components show similar trends across the 2 classes (and across test and training data). As evident from the plot, the MSE of the reconstructed face reduces as the number of prinicpal components increases and saturates after a certain point (approx 40). This number matches the basis size we choose based on the singular value plot. As indicated before, the first 40 principal components capture a significant part of the information in the data matrix. The difference across test set and trainig set experiments is the absolute MSE values. As expected, the error is more for test set when a totally new face is reconstructed.

PA(5a)
Generate 60 test images from data not used for training. First 60 images are neutral faces, last 60 are smiling faces

[20]:
```
# Create data for testing.
testData = np.concatenate([dataTrain_a[:,range(60)], dataTrain_b[:,range(60)]],␣
↪axis = 1)

# Ground truth =
gtLabels = np.hstack([np.ones((1,60)), np.zeros((1,60))])
```

PA(5b,c,d)

Classify test image as smiling (0) or neutral(1)

[21]:
```
predicted_labels = np.ones_like(gtLabels)*-1;
for i in range(120):
    # Predict on ith test image
    T = testData[:,[i]]
    # Find projections on 2 face space
    proj_a = reconstructFace(T,meanFace_a,eigen_faces_a_basis)
    proj_b = reconstructFace(T,meanFace_b,eigen_faces_b_basis)

    # Calculate MSE
    MSE_a = calculateMSE(proj_a, T)
    MSE_b = calculateMSE(proj_b, T)

    #print(MSE_a, MSE_b)
    if(MSE_a < MSE_b):
        # Predicted as neutral image
        predicted_labels[0,i] = 1;
    else:
        # Predicted as smiling image
        predicted_labels[0,i] = 0;
```

PA(5e)
Measure classification accuracy

[22]:
```
# Classification accuracy wrt neutral class
n_correct_a = np.sum(predicted_labels[0,range(60)] == 1)

# Classification accuracy wrt smiling class
n_correct_b = np.sum(predicted_labels[0,range(60,120)] == 0)

acc_a = n_correct_a/60*100
acc_b = n_correct_b/60*100

print('Accuracy w.r.t Neutral Face class ->' + str(acc_a))
print('Accuracy w.r.t Smiling Face class ->' + str(acc_b))

# Overall accuracy
n_correct_total = np.sum(predicted_labels == gtLabels)
acc_t = n_correct_total/120*100
print('Total classification accuracy ->' + str(acc_t))
```

```
Accuracy w.r.t Neutral Face class ->70.0
Accuracy w.r.t Smiling Face class ->100.0
Total classification accuracy ->85.0
```

PA(5f) Plot mis-classified image

[23]:
```python
# Neutral face mislabeled as smiling
idx_mis_a = np.where(predicted_labels[0,range(60)] == 0)
img = testData[:,[idx_mis_a[0][0]]]
plotImage(img.reshape(m,n), 'Neutral mislabeled as smiling')

# Smiling face mislabeled as neutral
#idx_mis_b = np.where(predicted_labels[0,range(60,120)] == 1)
img = testData[:,[idx_mis_a[0][0]+59+1]]
plotImage(img.reshape(m,n), 'Smiling mislabeled as neutral')
```

Neutral mislabeled as smiling

The 2 faces have significant similarity which may be leading to misclassification.

A possible way to improve the performance is to capture more faces across the classes in the test set to generate a better basis approximation of the 2 face-spaces (sub-spaces)