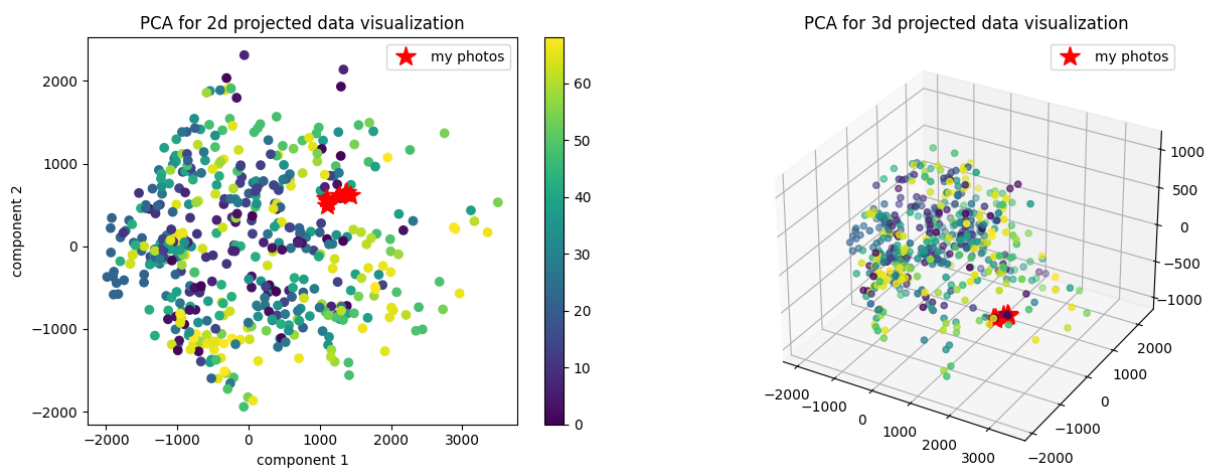


Q1: PCA

The 25 subjects that I choose to process are with labels:

49, 7, 48, 10, 65, 39, 63, 34, 13, 1, 43, 68, 21, 54, 22, 28, 27, 38, 61, 58, 3, 66, 26, 14, 40.

(a) PCA based data distribution visualization

The above two images are 2d and 3d projected data visualization respectively. I highlight my own photos by using red stars, and circles with different colors correspond to different groups. The image below shows the corresponding 3 eigenfaces used for the dimensionality reduction.

3 eigenfaces**(b) PCA plus nearest neighbor classification results**

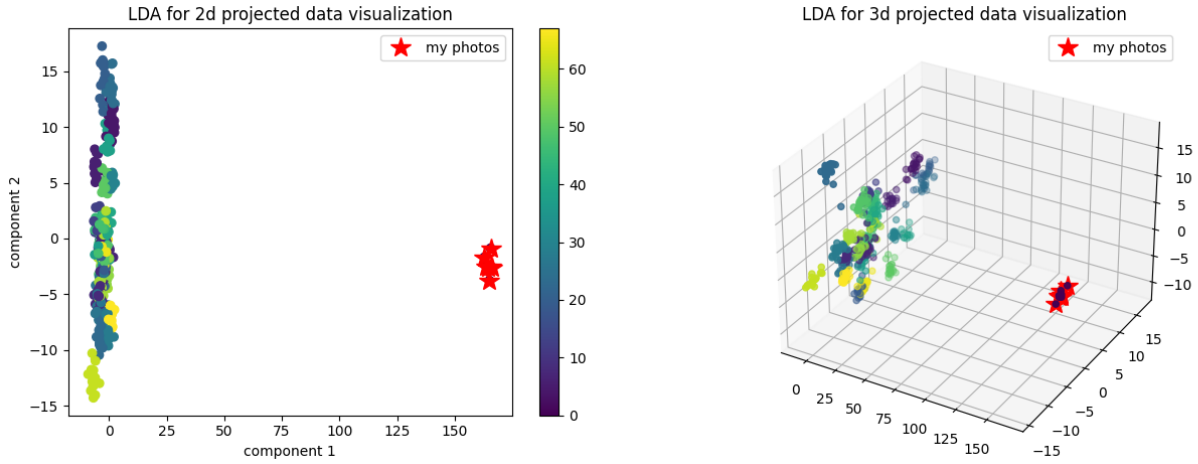
Classification accuracy	CMU PIE test images	my own photos
dim = 40	94.45%	100.00%
dim = 80	95.61%	100.00%
dim = 200	96.07%	100.00%

The table shows the classification accuracy on the CMU PIE test images and my own photo separately with the reduced dimension 40, 80 and 200 respectively. It indicates that the higher dimension PCA reduces to, the higher accuracy will the test images have. But they are almost the same and all retain a high accuracy level.

Q2: LDA

The 25 subjects that I choose to process are with labels:

59, 56, 49, 6, 47, 4, 8, 7, 13, 58, 50, 38, 24, 61, 65, 37, 30, 19, 67, 28, 23, 26, 45, 20, 40.

(a) LDA based data distribution visualization

The above two images are 2d and 3d projected data visualization by LDA respectively. I highlight my own photos by using red stars, and circles with different colors correspond to different groups.

(b) LDA plus nearest neighbor classification results

Classification accuracy	CMU PIE test images	my own photos
dim = 2	21.42%	100.00%
dim = 3	43.53%	100.00%
dim = 9	89.91%	100.00%

The table shows the classification accuracy on the CMU PIE test images and my own photo separately with the reduced dimension 40, 80 and 200 respectively. From the accuracy, we can see that increasing the dimension can help to increase the classification accuracy significantly. Among these three dimensions, reducing to 9 dimension can obtain the highest classification accuracy.

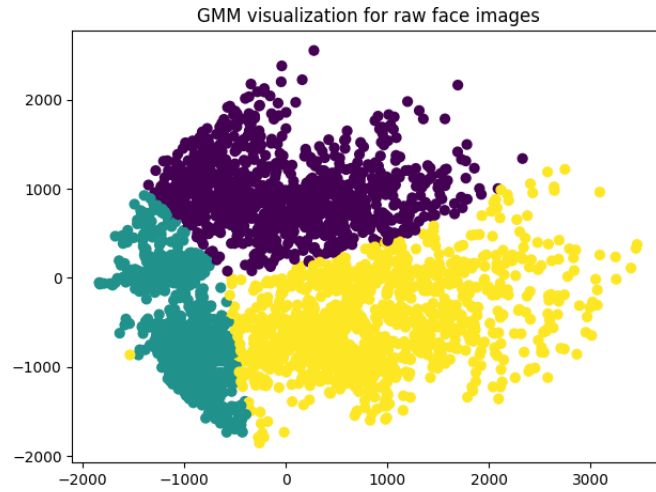
Q3: GMM for clustering

To visualize the clustering results and the images assigned to the Gaussian components, I firstly project each vectorized face images to a 2d plane, then plot 2d clustering results from GMM, lastly I randomly choose 3 images that are assigned to the same component respectively for visualization.

The 25 subjects that I choose to process are with labels:

24, 50, 68, 32, 54, 51, 31, 28, 58, 6, 1, 49, 37, 40, 39, 38, 8, 26, 4, 27, 3, 52, 14, 65, 64.

For raw face images, the GMM visualization and randomly sampled images are shown below:



raw face images assigned to the 1st Gaussian component

raw face images assigned to the 2nd Gaussian component

raw face images assigned to the 3rd Gaussian component

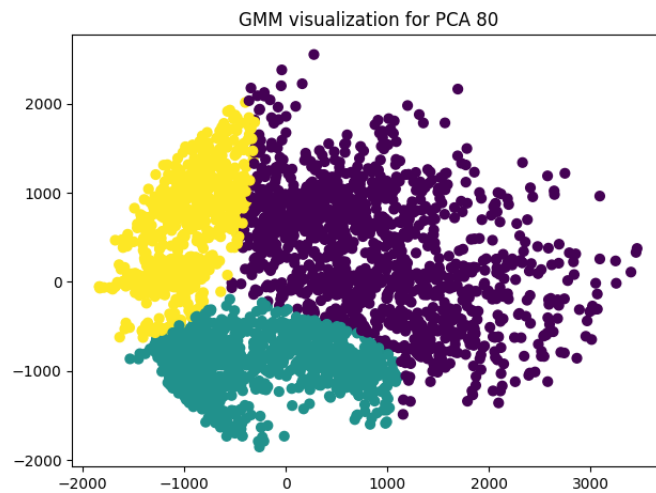


Figure 1: raw face images assigned to the 1st component

Figure 2: raw face images assigned to the 2nd component

Figure 3: raw face images assigned to the 3rd component

For PCA 80, the GMM visualization and randomly sampled images are shown below:



PCA 80 assigned to the 1st Gaussian component



PCA 80 assigned to the 2nd Gaussian component



PCA 80 assigned to the 3rd Gaussian component

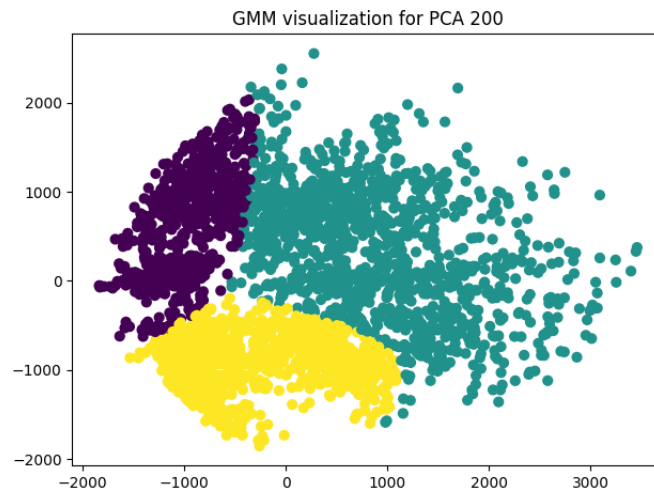


Figure 4: PCA 80 assigned to the 1st Gaussian component

Figure 5: PCA 80 assigned to the 2nd Gaussian component

Figure 6: PCA 80 assigned to the 3rd Gaussian component

For PCA 200, the GMM visualization and randomly sampled images are shown below:



PCA 200 assigned to the 1st Gaussian component



PCA 200 assigned to the 2nd Gaussian component



PCA 200 assigned to the 3rd Gaussian component



Figure 7: PCA 200 assigned to the 1st Gaussian component

Figure 8: PCA 200 assigned to the 2nd Gaussian component

Figure 9: PCA 200 assigned to the 3rd Gaussian component

Q4: SVM

(a) SVM classification results with different parameter values

The 25 subjects that I choose to process are with labels:

35, 16, 50, 59, 2, 68, 62, 4, 47, 29, 67, 56, 27, 44, 19, 63, 23, 41, 60, 13, 46, 31, 38, 10, 65.

I notice that the default parameter “max_iter” is 1000, if do not increase the iterations, the program will report warnings: Liblinear failed to converge. Therefore, to compare the effect of data dimension and parameter C on the final classification accuracy, I focus on two parts: one is the convergence rate, and another is the final accuracy.

For the convergence rate, I compare the accuracy with the same training iterations: **1000**. For the final accuracy, I increase the parameter “max_iter” to **10000** and record the final accuracy.

The classification accuracy on **1000** iterations with different parameters C and dimensions are shown below:

Classification accuracy	raw face images	PCA 80	PCA 200
$C = 0.01$	98.92%	58.49%	81.94%
$C = 0.1$	98.92%	62.64%	86.70%
$C = 1$	98.92%	60.49%	87.09%

The classification accuracy on **10000** iterations with different parameters C and dimensions are shown below:

Classification accuracy	raw face images	PCA 80	PCA 200
$C = 0.01$	98.92%	91.01%	90.78%
$C = 0.1$	98.92%	88.78%	84.01%
$C = 1$	98.92%	75.40%	88.78%

From the above two tables, I conclude that:

1. When fix the penalty parameter C , the larger the data dimension is, the higher accuracy will SVM obtain.
2. When fix the penalty parameter C , the larger the data dimension is, the faster will SVM converges.
3. When fix data dimension, the penalty parameters have no effect on raw face images.
4. When fix data dimension, $C = 0.01$ is the best penalty parameters for PCA 80 and PCA 200 to get the highest accuracy.
5. When fix data dimension, $C = 0.01$ is the best penalty parameters to get the fastest convergence rate compared with the other parameters.

Q5: CNN**(a) CNN classification results with different network architectures**

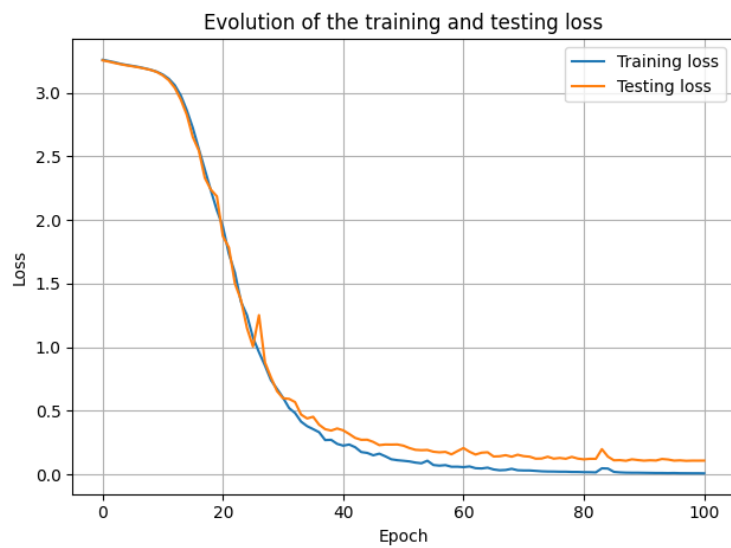
The 25 subjects that I choose to process are with labels:

35, 16, 50, 59, 2, 68, 62, 4, 47, 29, 67, 56, 27, 44, 19, 63, 23, 41, 60, 13, 46, 31, 38, 10, 65.

The following table shows the training loss and testing loss during training. I train the neural network with 100 epochs.

Epoch	Training Loss	Testing Loss
0	3.26	3.25
20	1.95	1.87
40	0.23	0.35
60	0.06	0.21
80	0.02	0.12
100	0.008	0.11

I also draw the training loss and testing loss curves:



The final classification performance is as follows:

Final training accuracy	Final testing accuracy
100.00%	97.54%