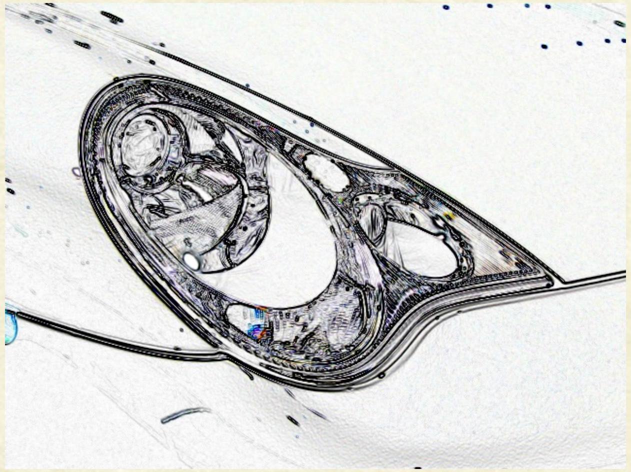
CS7.505: Computer Vision

Spring 2022: Face Detection and Recognition



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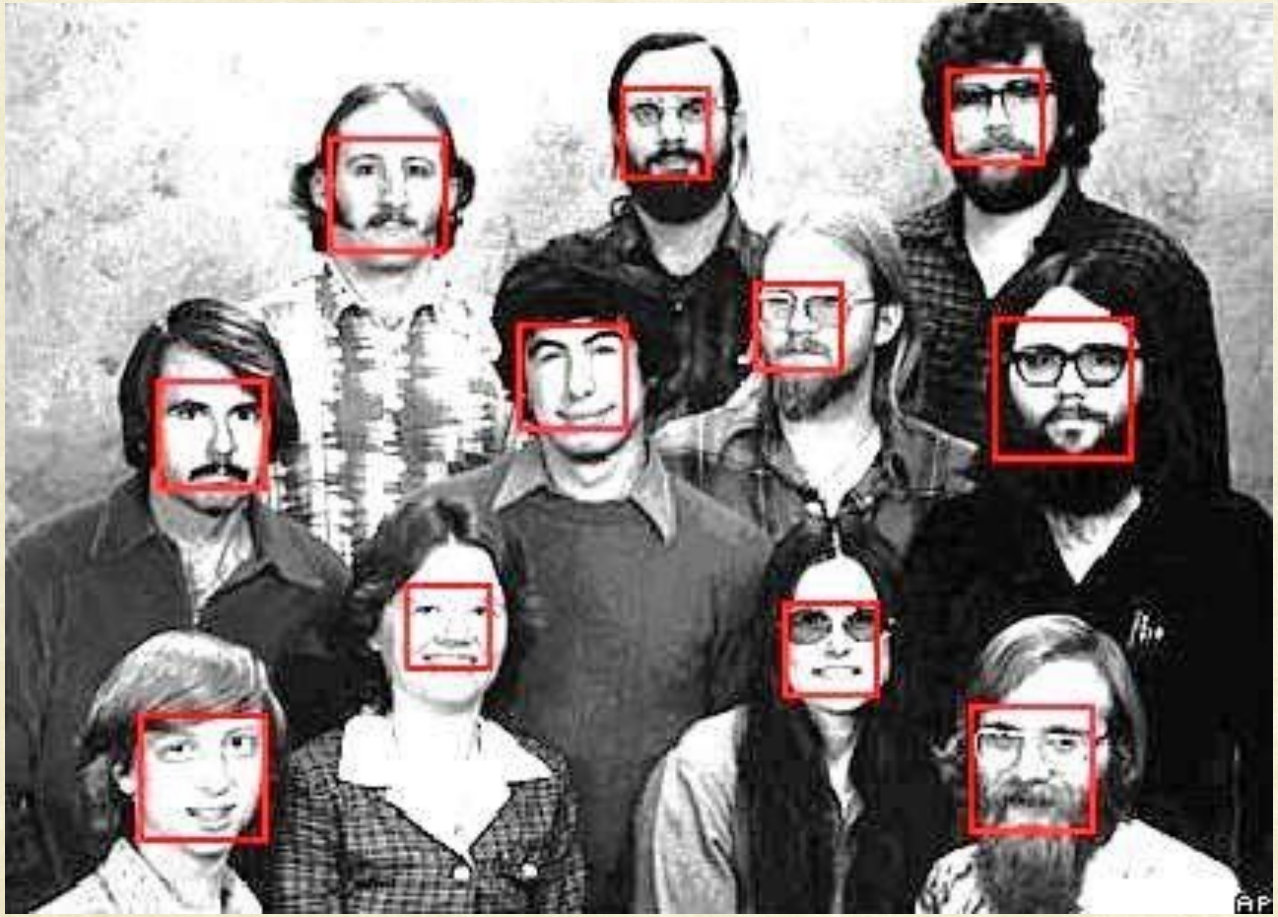
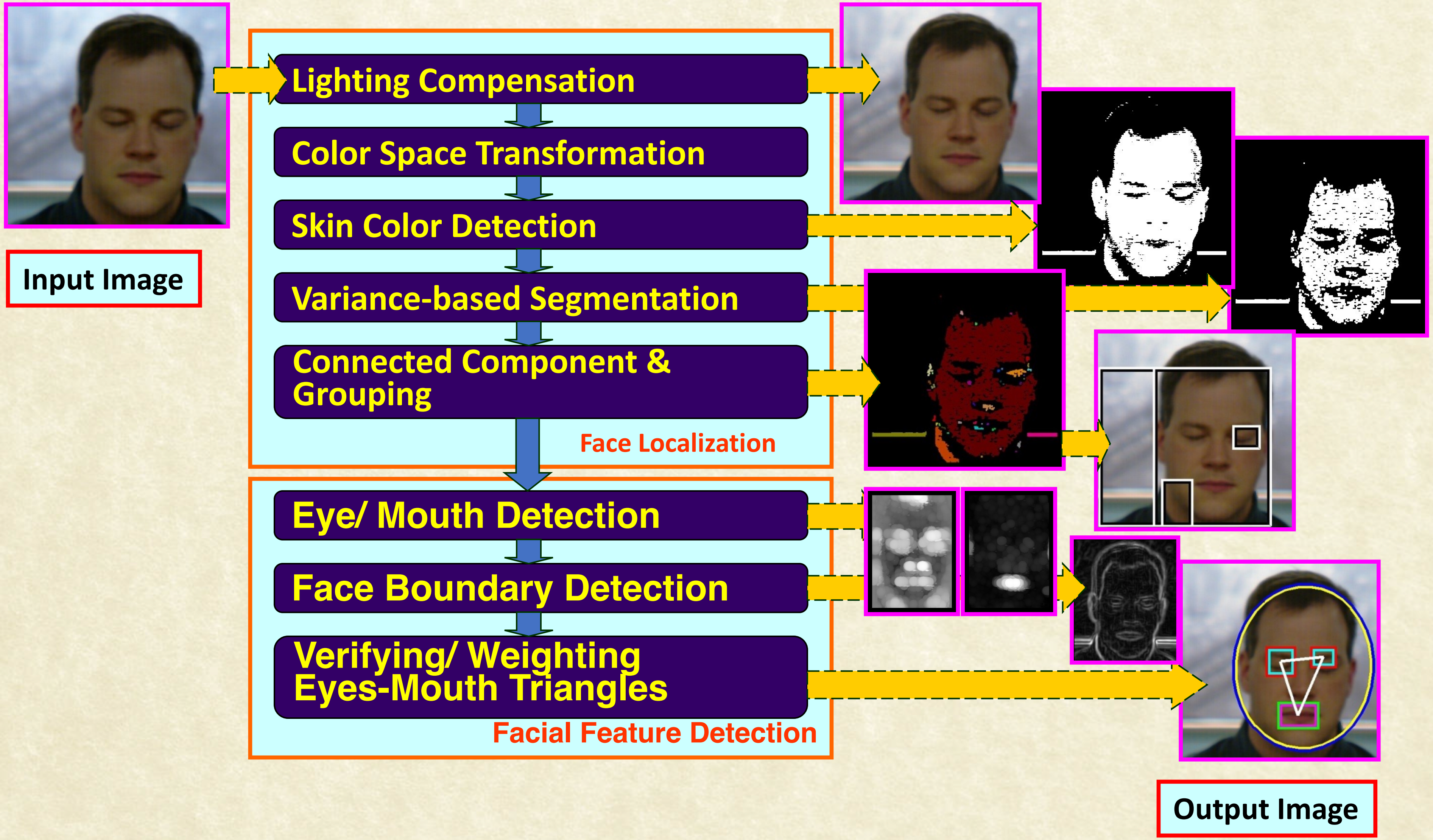
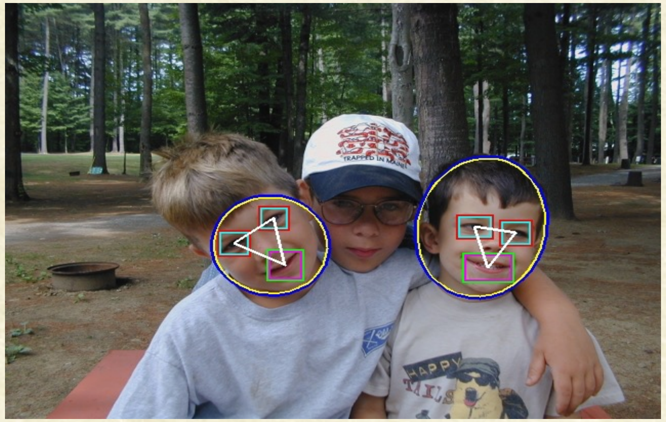
Face Detection



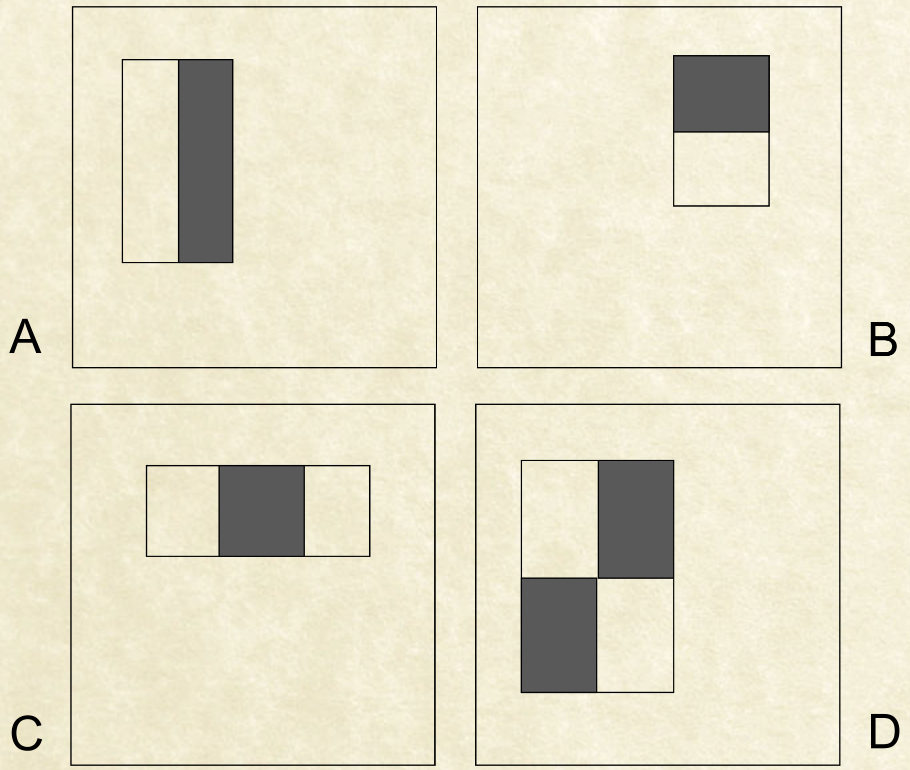
Face Detection Using Skin Color



Face Detection Using Skin Color

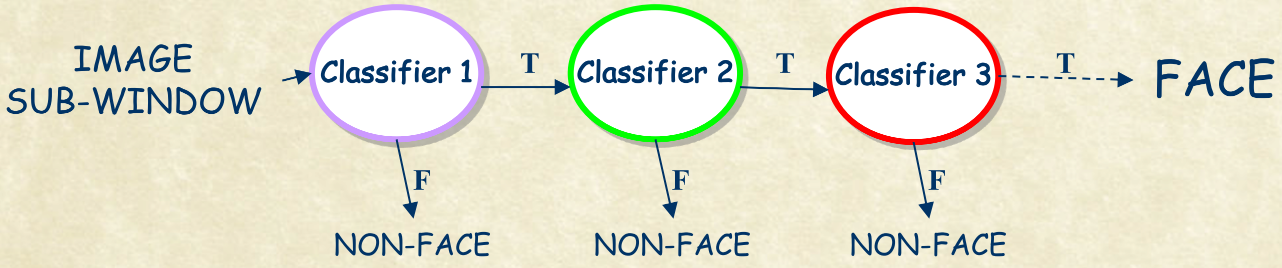


Viola and Jones Detector



Rectangular filters

$$f(x,y) = \sum_i p_b(i) - \sum_i p_w(i)$$



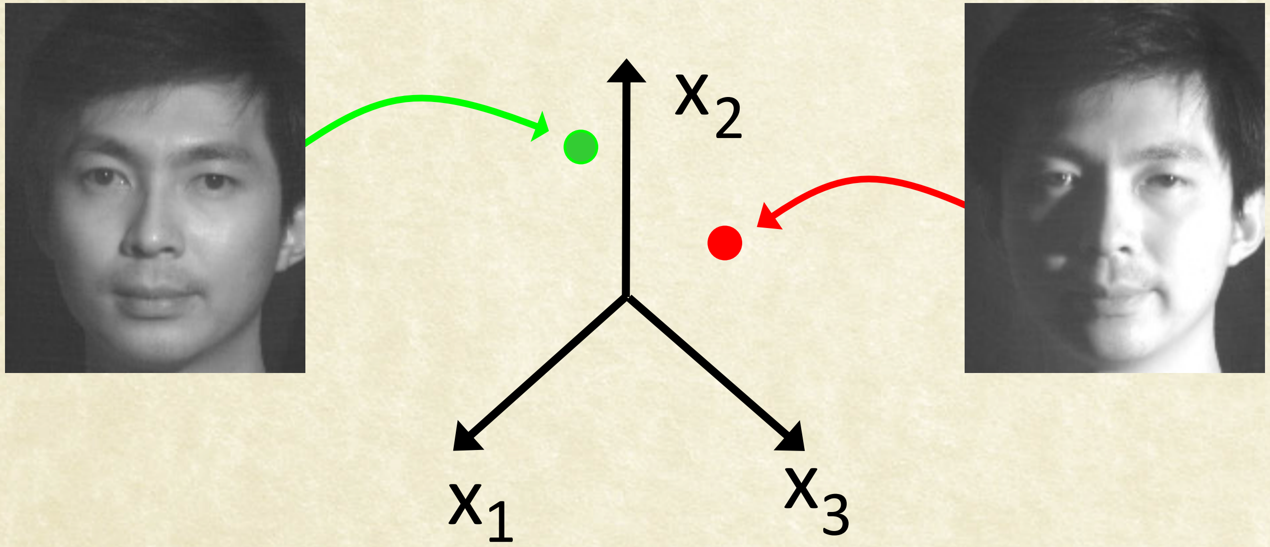
Face Recognition vs. Verification

- Face Authentication/Verification (1:1 matching)

- Face Identification/Recognition (1:N matching)

Image as a Feature Vector

- Consider an n-pixel image to be a point in an n-dimensional space, $\mathbf{x} \in \boldsymbol{R}^n$. Each pixel value is a coordinate of $\mathbf{x}$.
- Use Nearest Neighbor Classifier
- What is the problem?



$\{ R_j \}$ are set of training images.

$$ID = \arg\min_j dist(R_j, I)$$

Intra-Class Variability



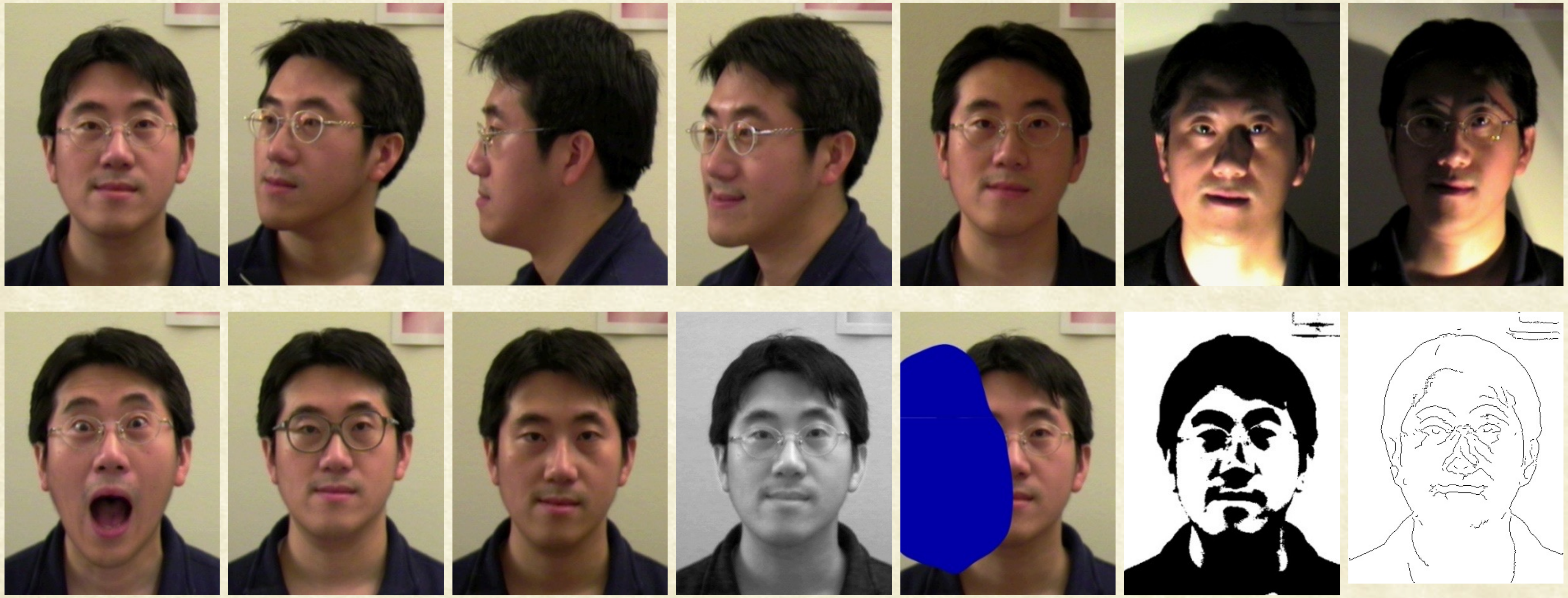







Intra-Class Variability

- Faces with intra-subject variations in pose, illumination, expression, accessories, color, occlusions, and brightness



Inter-Class Similarity

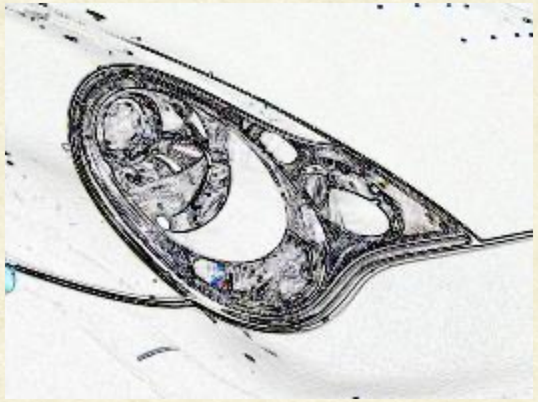
www.marykateandashley.com

news.bbc.co.uk/hi/english/in_depth/americas/2000/us_elections

Twins

Father and son

Eigen Faces for Recognition



Covariance : m samples, n features

Vectors 1 and 3 Cell (3, 1) or (1, 3)

$$A = \begin{bmatrix} 1 & 3 & 5 \\ 5 & 4 & 1 \\ 3 & 8 & 6 \end{bmatrix} \quad \xrightarrow{\text{Covariance}} \quad \begin{bmatrix} 2.67 & 0.67 & -2.67 \\ 0.67 & 4.67 & 2.33 \\ -2.67 & 2.33 & 4.67 \end{bmatrix}$$

Covariance Matrix

Variance:

$$s^2 = \frac{\sum (\overline{X} - X_i)^2}{N}$$

Covariance:

$$cov(\mathbf{X}, \mathbf{Y}) = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})$$

$$Cov(M_a, M_b) = \frac{1}{m} \sum_{i=1}^{m} (q_{i,a} - \overline{q_a})(q_{i,b} - \overline{q_b})$$

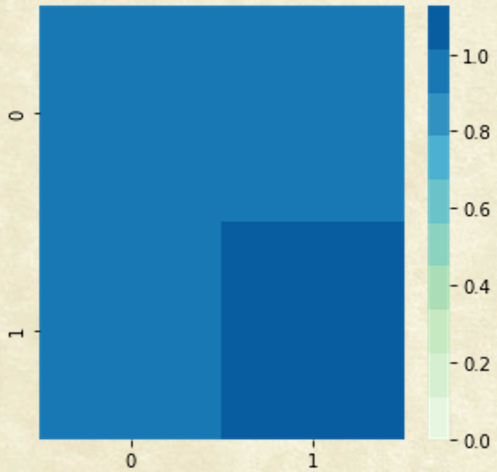
$$\begin{bmatrix} 0.39701 & 0.51117 \\ 0.55582 & 0.93003 \\ 0.59403 & 0.96645 \\ 0.51544 & 0.29759 \\ 0.85313 & 0.18118 \\ 0.88564 & 0.69114 \end{bmatrix}$$

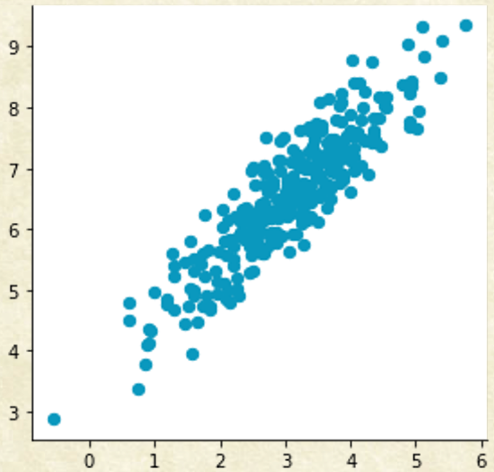
$$\begin{pmatrix} & M1 & M2 & M3 & \dots & Mn \\ S1 & q_{1,1} & q_{1,2} & q_{1,3} & \dots & q_{1,n} \\ S2 & q_{2,1} & q_{2,2} & q_{2,3} & \dots & q_{2,n} \\ S3 & q_{3,1} & q_{3,2} & q_{3,3} & \dots & q_{3,n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ Sm & q_{m,1} & q_{m,2} & q_{m,3} & & q_{m,n} \end{pmatrix} \Rightarrow C = \begin{pmatrix} \mathrm{cov}(M_1,M_1) & \mathrm{cov}(M_1,M_2) & \cdots & \mathrm{cov}(M_1,M_n) \\ \mathrm{cov}(M_2,M_1) & \mathrm{cov}(M_2,M_2) & \cdots & \mathrm{cov}(M_2,M_n) \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(M_n,M_1) & \mathrm{cov}(M_n,M_2) & \cdots & \mathrm{cov}(M_n,M_n) \end{pmatrix}_{n \times n}$$

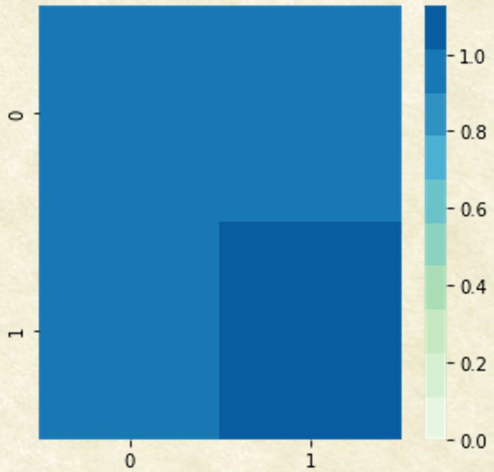
N-dimensional Covariance Matrix

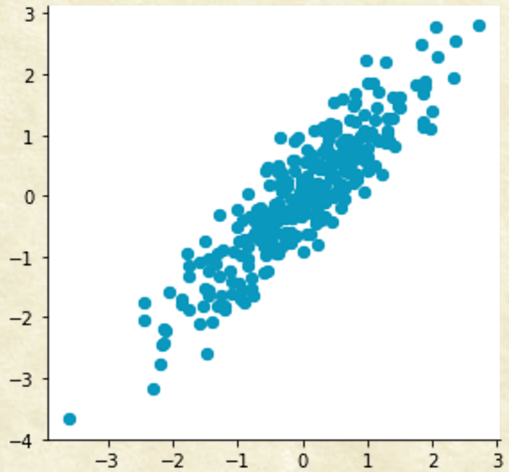
Mean Normalization

$$\boldsymbol{X}' = \boldsymbol{X} - \bar{x}$$









$$C = \begin{bmatrix} +0.95 & +0.92 \\ +0.92 & +1.12 \end{bmatrix}$$

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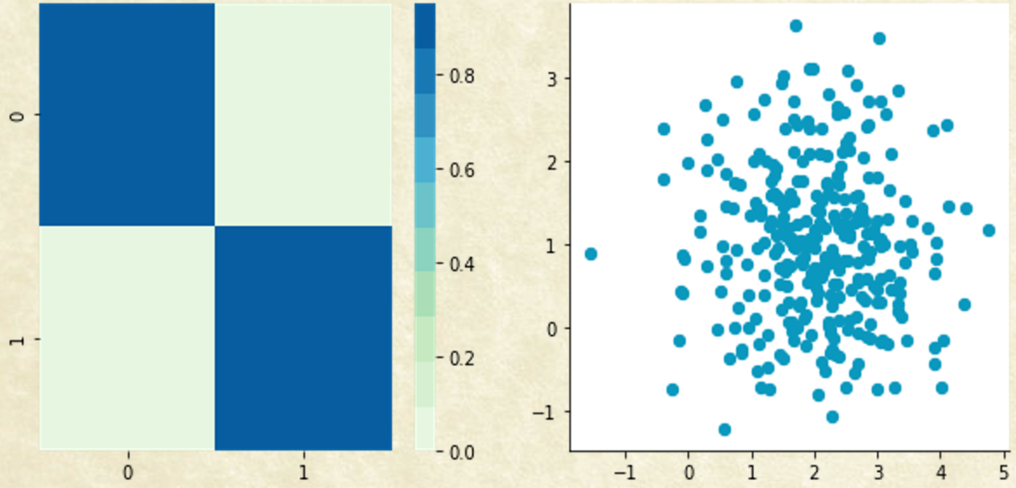
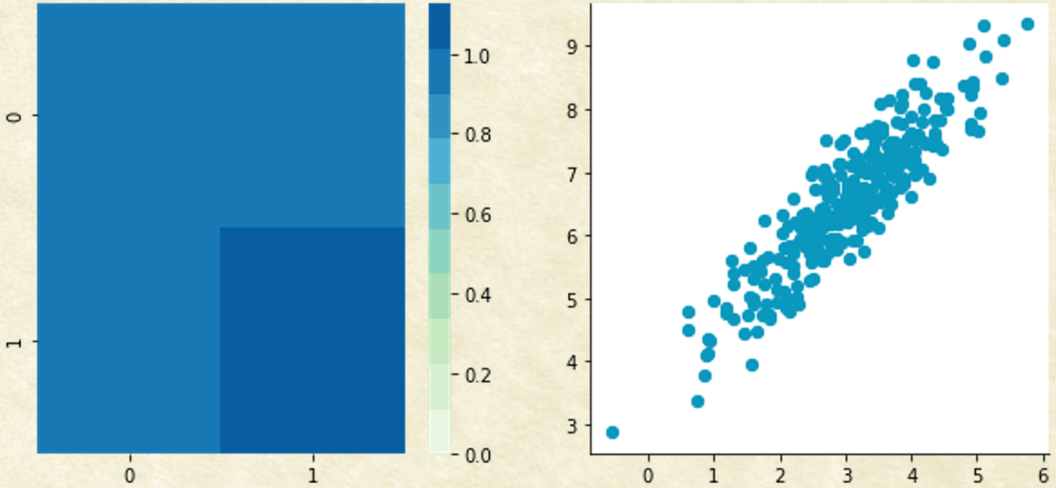
Covariance Matrix

- The off-diagonal elements give insights into the spread of data points in the feature space

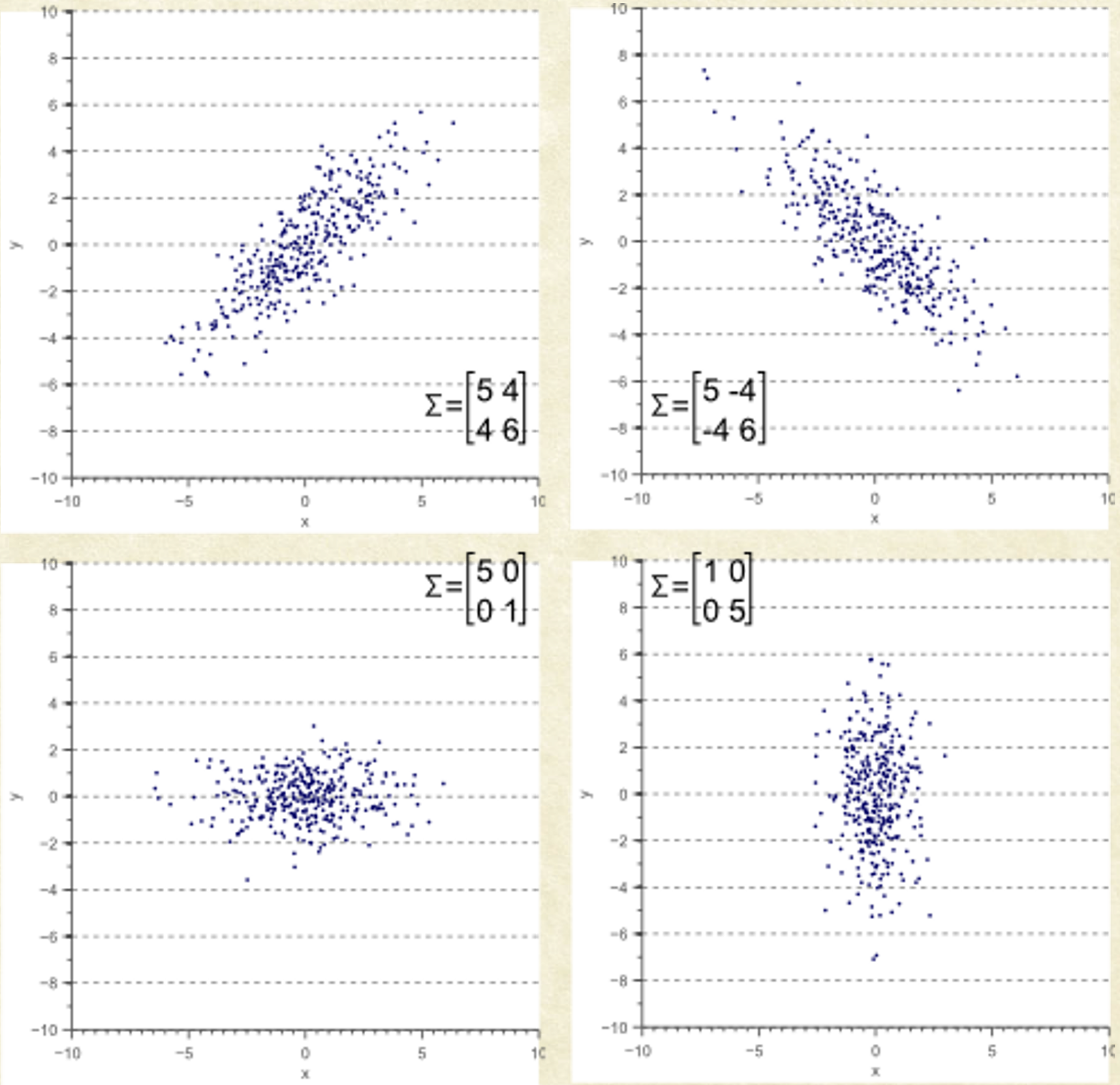




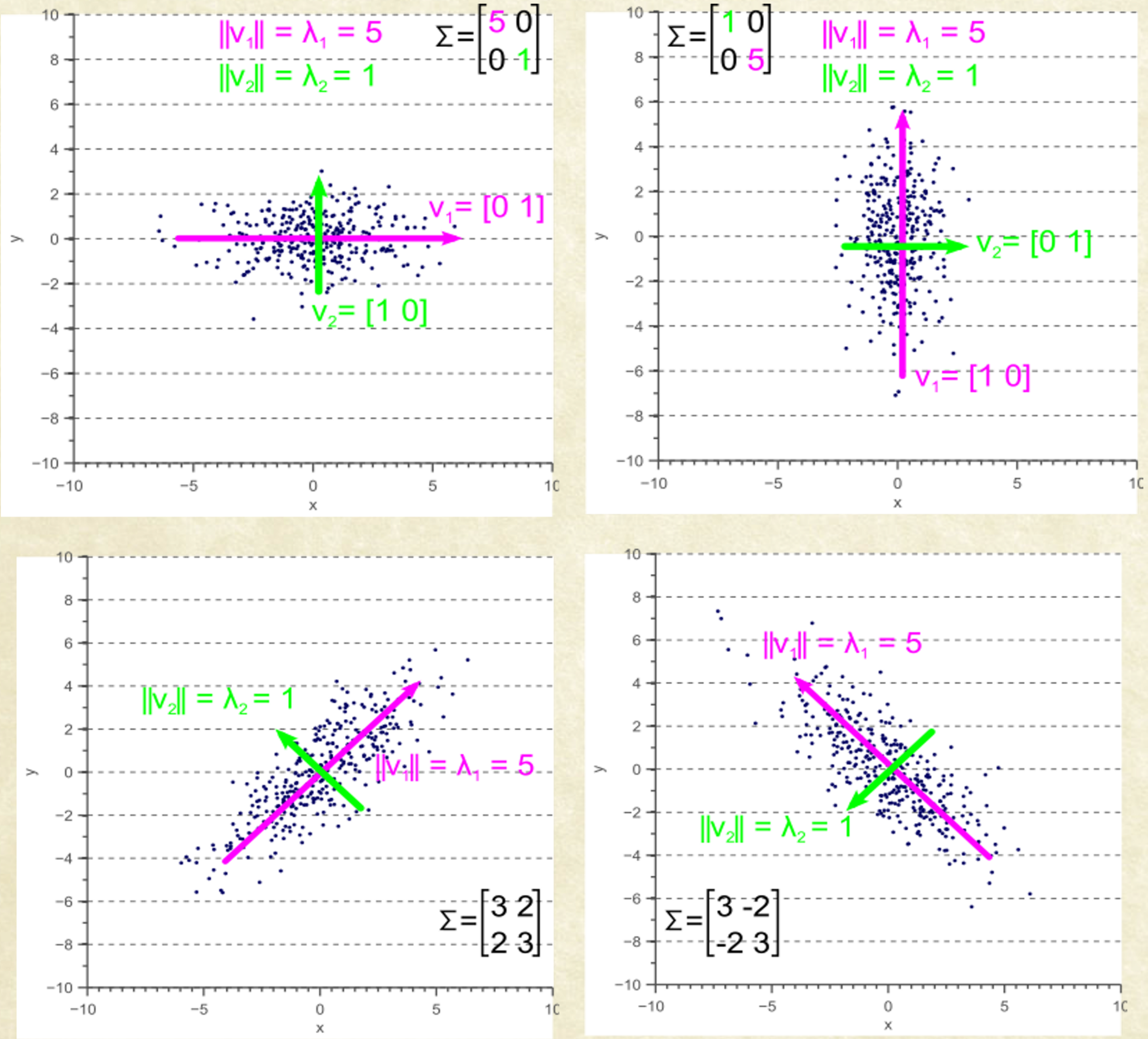
$$C = \begin{bmatrix} +0.95 & -0.04 \\ -0.04 & +0.87 \end{bmatrix}$$

$$C = \begin{bmatrix} +0.95 & +0.92 \\ +0.92 & +1.12 \end{bmatrix}$$

Covariance Matrix and Data Distribution



Eigen Analysis of Covariance Matrix

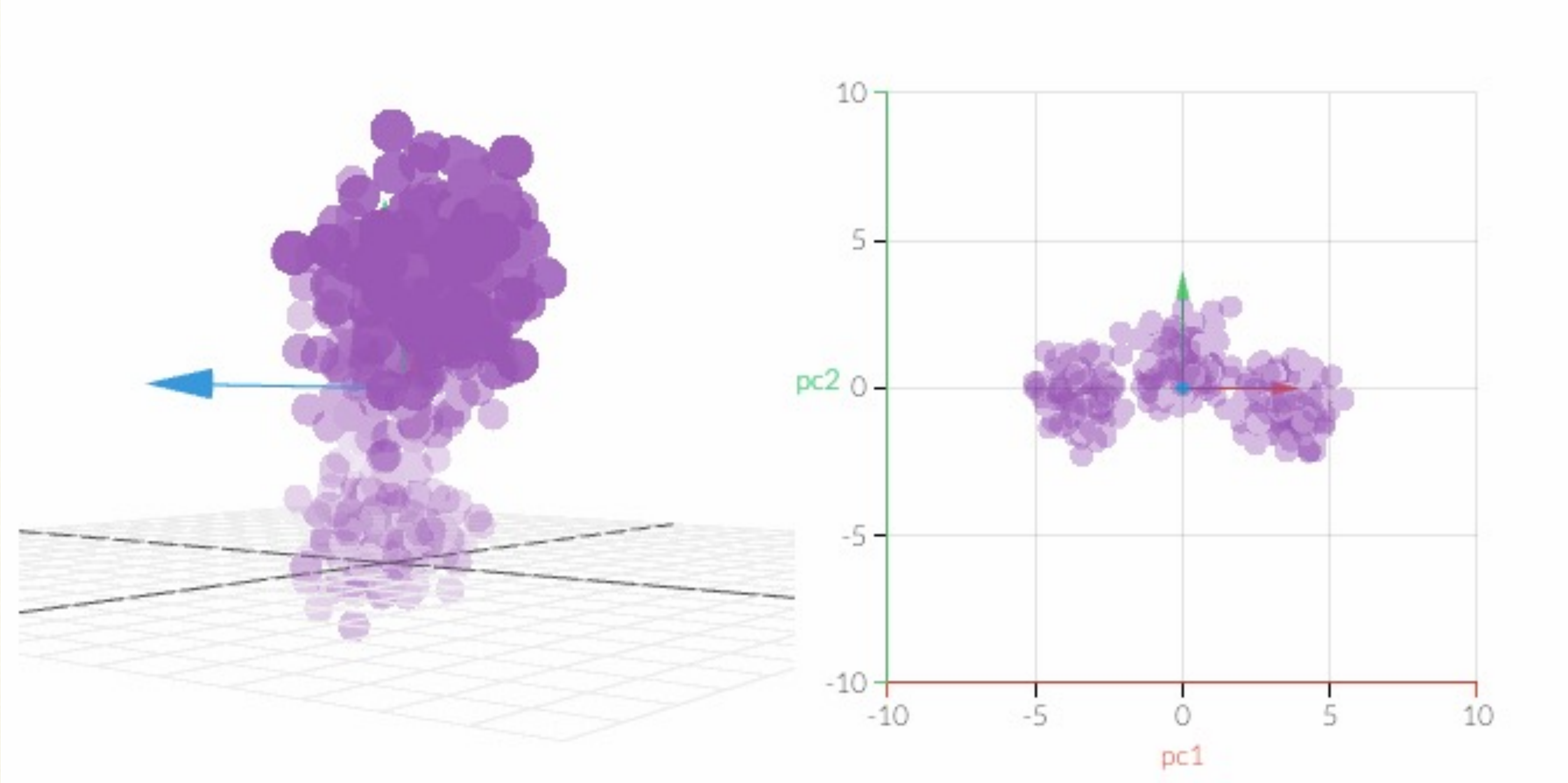


$$\Sigma\vec{v} = \lambda\vec{v}$$

Value of λ indicates `variance' (spread) in direction of eigenvector v associated with λ

v_1, v_2: *Principal Components*

3D to 2D



X1, X2, X3

Z1, Z2

PCA based Feature Extraction

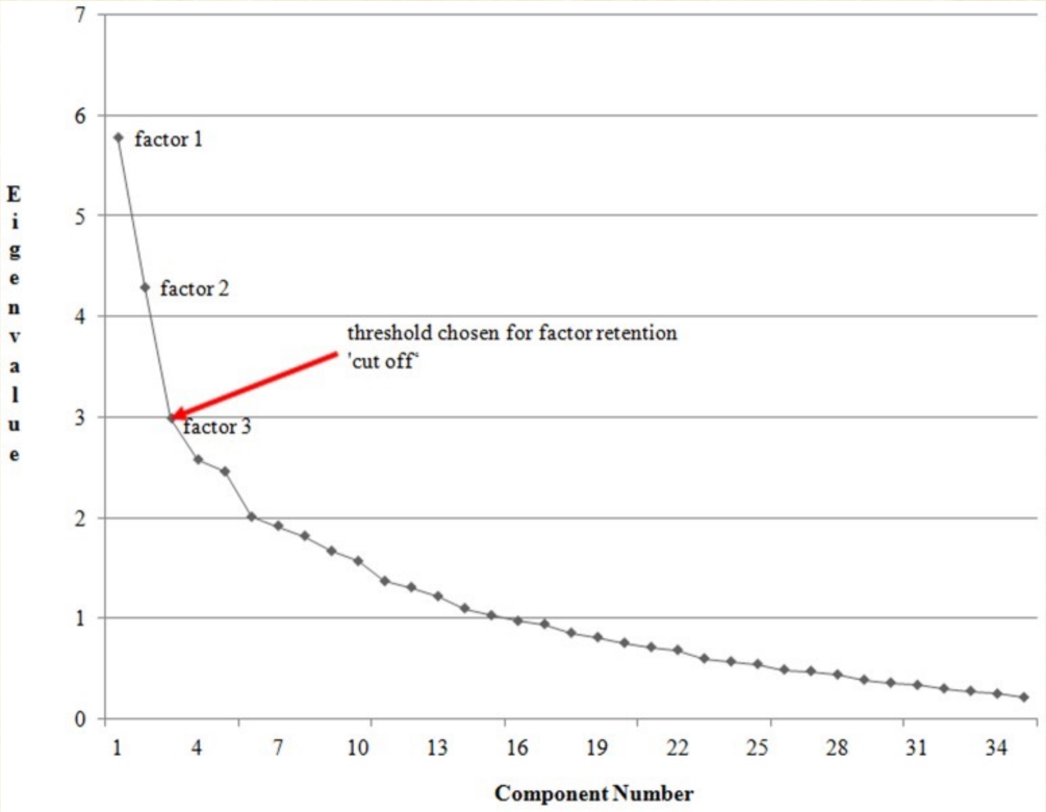
$$\overset{r \times 1}{\underset{Z}{\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ . \\ . \\ z_r \end{bmatrix}}} = \overset{r \times d}{\underset{U}{\begin{bmatrix} u_{11} & u_{12} & u_{13} & . & . & . & . & . & u_{1d} \\ u_{21} & u_{22} & u_{23} & . & . & . & . & . & u_{2d} \\ u_{31} & u_{32} & u_{33} & . & . & . & . & . & u_{3d} \\ . & & & & & & & & \\ u_{r1} & u_{r2} & u_{r3} & . & . & . & . & . & u_{rd} \end{bmatrix}}} \overset{d \times 1}{\underset{X}{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ . \\ . \\ . \\ . \\ . \\ . \\ . \\ x_d \end{bmatrix}}}$$

Each row in U is an eigen vector of co-variance Matrix

Appreciating PCA: Two Questions

$$\text{Eg.} \frac{\sum_{i=1}^{r} \lambda_i}{\sum_{i=1}^{d} \lambda_i} > 0.90$$

- How many Eigen vectors to select?
  - Ans: Eigen Vectors corresponding to the r largest Eigen values
- How much information is lost? Can we recover the old data/ information from the Low-D point?



$$\mathbf{x} = z_1\mathbf{u_1} + z_2\mathbf{u_2} + z_3\mathbf{u_3} + z_4\mathbf{u_4}$$

$$\mathbf{x} = z_1\mathbf{u_1} + z_2\mathbf{u_2} + z_3\mathbf{u_3} + z_4\mathbf{u_4}$$

$$\mathbf{x}' = z_1\mathbf{u_1} + z_2\mathbf{u_2}$$

$$\text{Loss in Information} = ||\mathbf{x} - \mathbf{x}'||$$

Note: z_3 and z_4 are small and also λ_3 and λ_4 are small

https://www.researchgate.net/profile/Collins_Ouma/publication/263548435/figure/fig1/AS:202705835433990@1425340245309/A-Scree-plot-of-eigenvalues-of-the-unrotated-factors-displaying-an-elbow-of-the-plot.png

Application to Faces

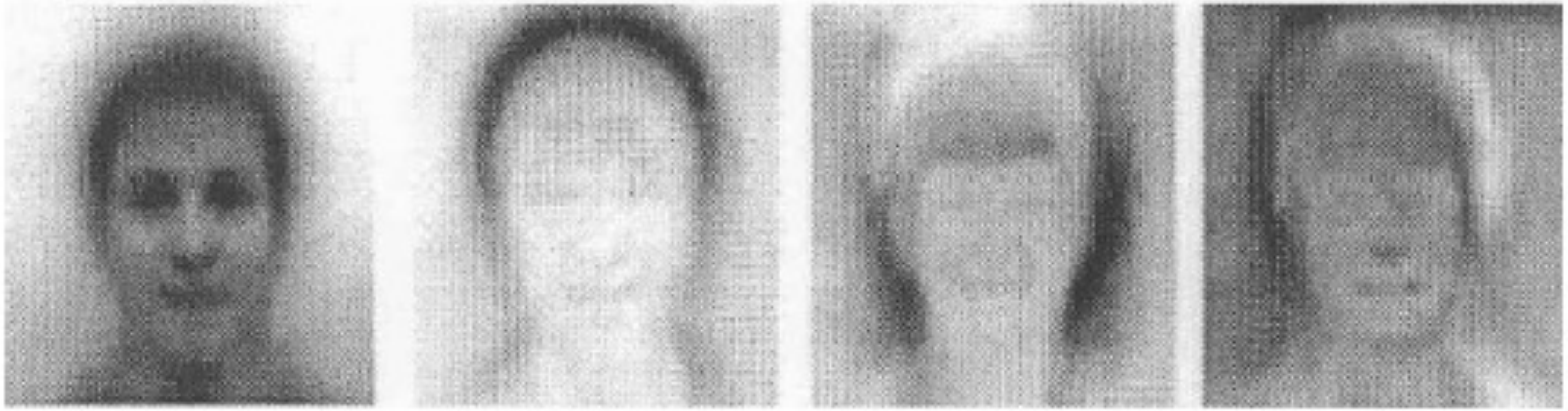
- Representing faces onto this basis

- Face reconstruction:

- Each face (minus the mean) Φ_i in the training set can be represented as a linear combination of the best K eigenvectors:

$$\hat{\Phi}_i - mean = \sum_{j=1}^{K} w_j u_j, \quad (w_j = u_j^T \Phi_i)$$

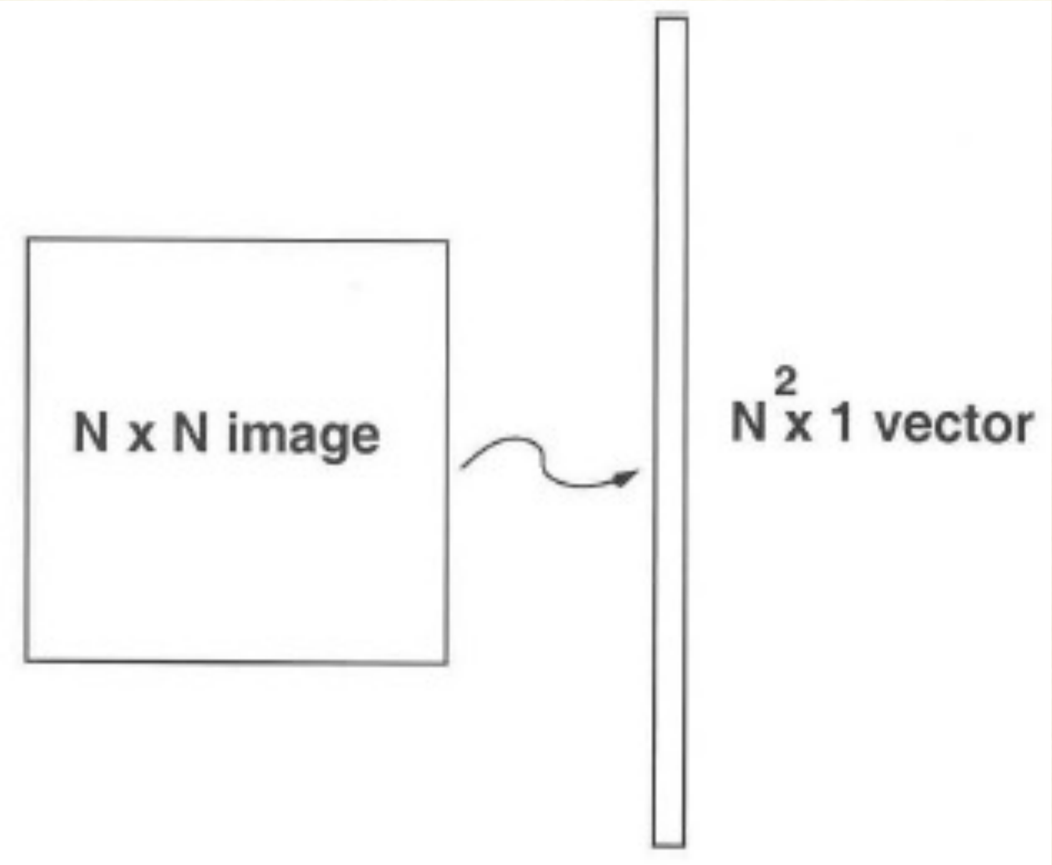
(we call the u_j's *eigenfaces*)



Eigenfaces

– M. Turk, A. Pentland, "Eigenfaces for Recognition", *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71-86, 1991.

- Face Recognition
  - The simplest approach is to think of it as a template matching problem
  - Problems arise when performing recognition in a high-dimensional space.
  - Significant improvements can be achieved by first mapping the data into a *lower dimensionality* space.



Face Recognition using Eigenfaces

- Given an unknown face image Γ (centered and of the same size like the training faces) follow these steps:

Step 1: normalize Γ: $\Phi = \Gamma - \Psi$

Step 2: project on the eigenspace

$$\hat{\Phi} = \sum_{i=1}^{K} w_i u_i \quad (w_i = u_i^T \Phi) \qquad (where \| u_i \| = 1)$$

Step 3: represent Φ as: $\Omega = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_K \end{bmatrix}$

Step 4: find $e_r = \min_l \|\Omega - \Omega^l\|$ $\qquad \| \Omega - \Omega^l \| = \sum_{i=1}^{K} (w_i - w_i^l)^2$

Step 5: if $e_r < T_r$, then Γ is recognized as face l from the training set.

Challenge 2: Computing Eigen Vectors

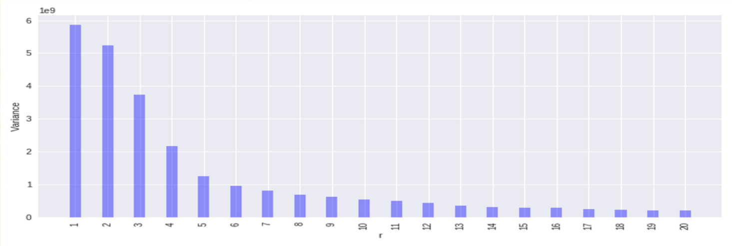
- For an NxN image (say 256 x 256), each feature vector is 65536 long
- Covariance matrix:
  - 65536 x 65536
- Training set: 16 classes, few hundred samples.

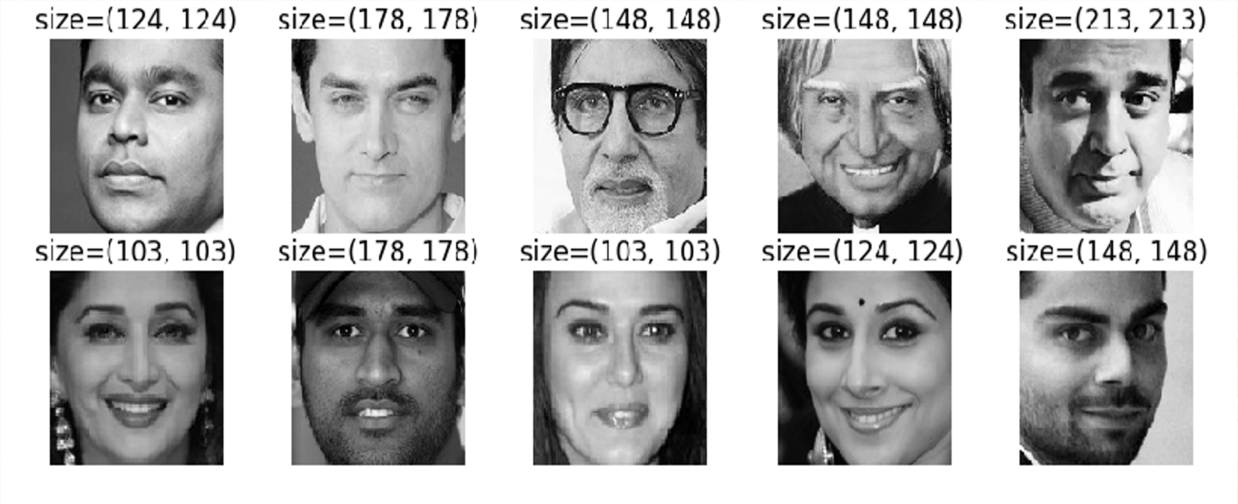
Eigenfaces

Mean Image

Basis Images

Recognize Indian Celebrities





- Rescale and Find mean of the face
- Find the Eigen Faces
- Find the weights to represent the face in Eigen space
- Reconstruct the image

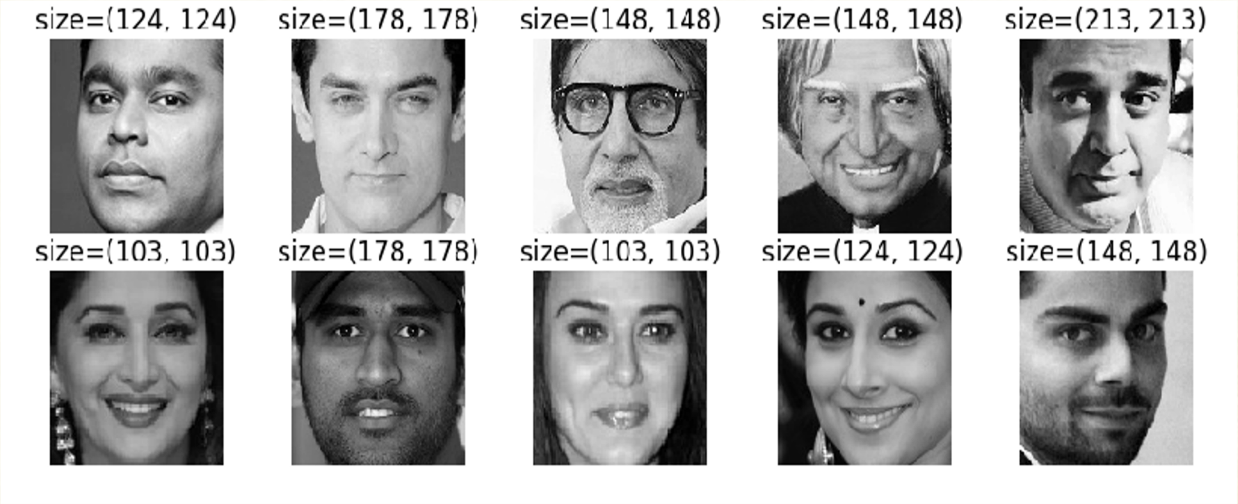
Eigen Vector 1

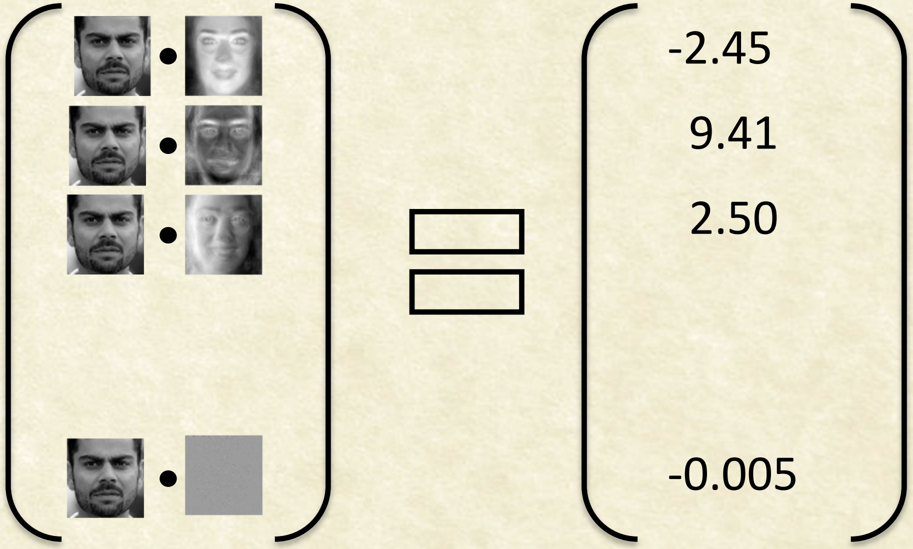
Eigen Vector 100

Eigen Vector 150

Eigen Vector 200

Recognize Indian Celebrities





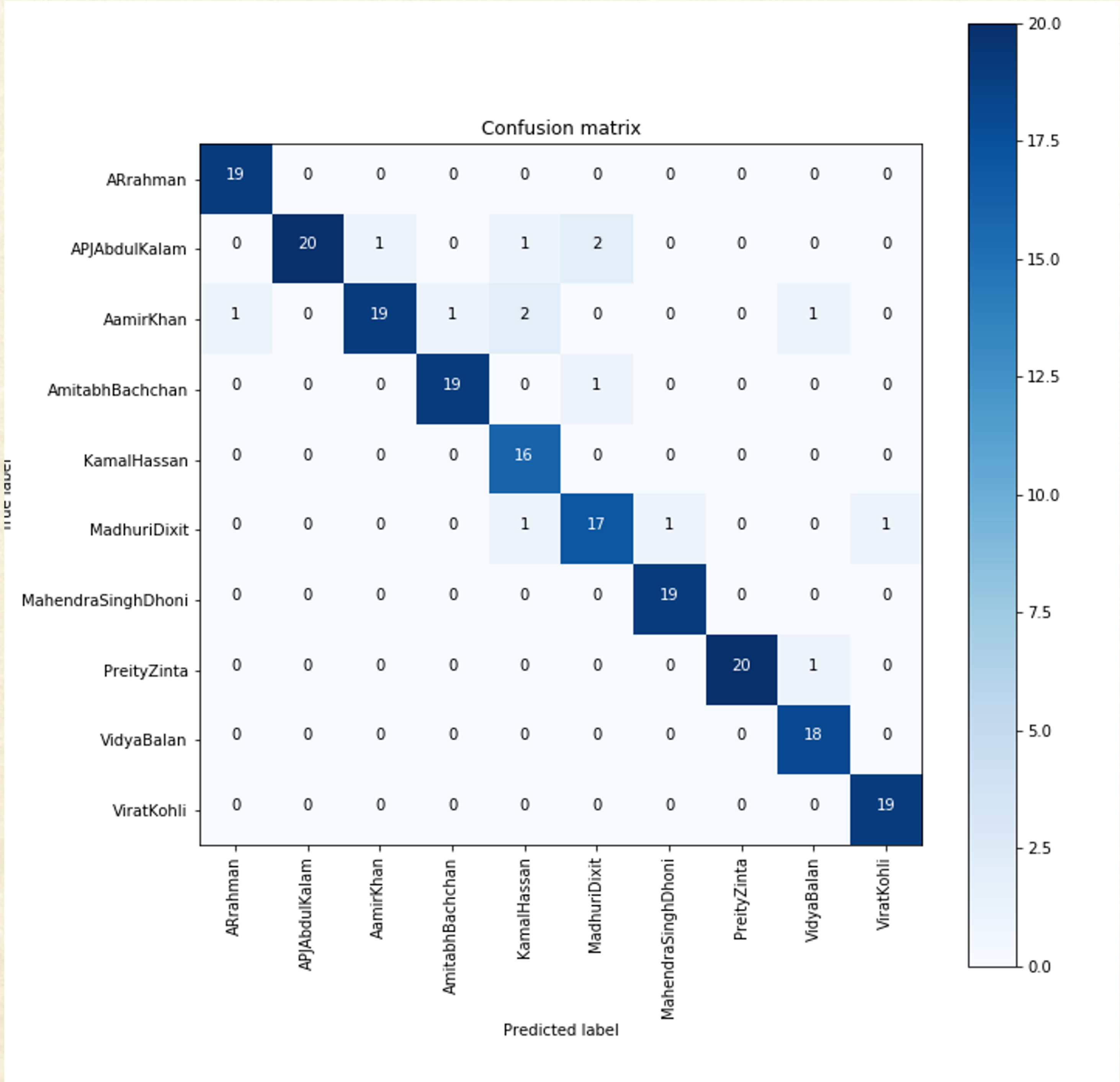
 =  + 

$$\hat{x} = \mu + w_1u_1+w_2u_2+w_3u_3+w_4u_4+ \ldots$$

Classification

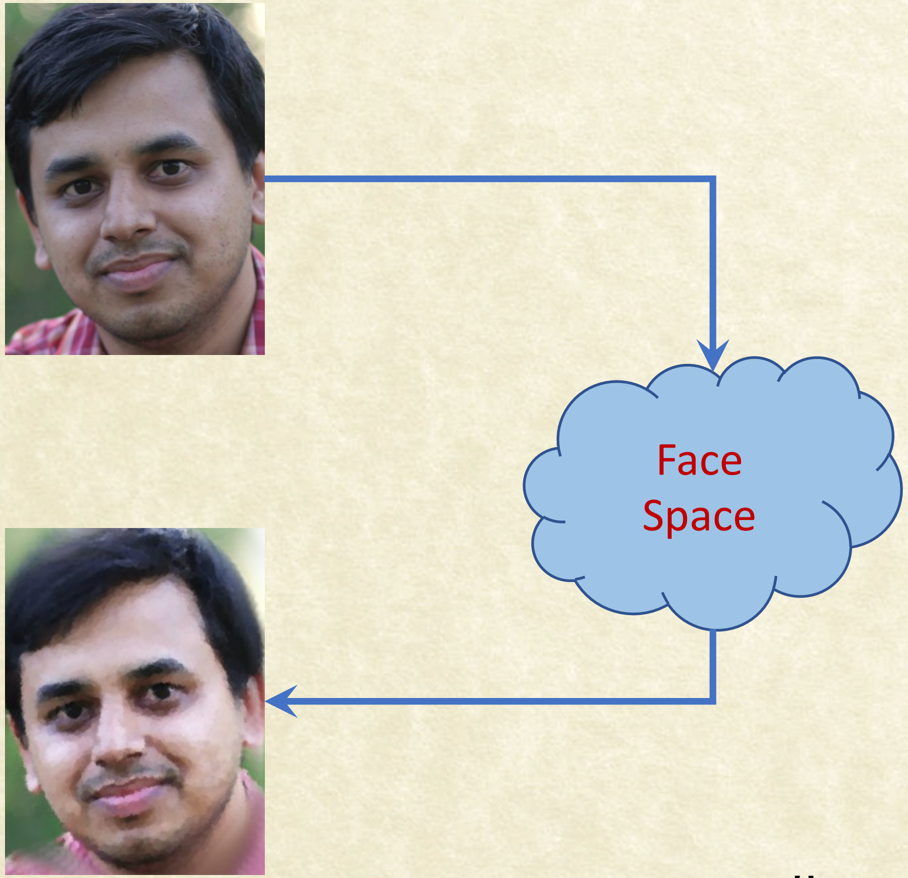
Training images: 400
Test images: 200

Accuracy: 96%



Face Detection using Eigenfaces

Φ



$\hat{\Phi}$

- Given an unknown image Γ

<u>Step 1:</u> compute $\Phi = \Gamma - \Psi$

<u>Step 2:</u> compute $\hat{\Phi} = \sum_{i=1}^{K} w_i u_i \quad (w_i = u_i^T \Phi)$

$(where \| u_i \| = 1)$

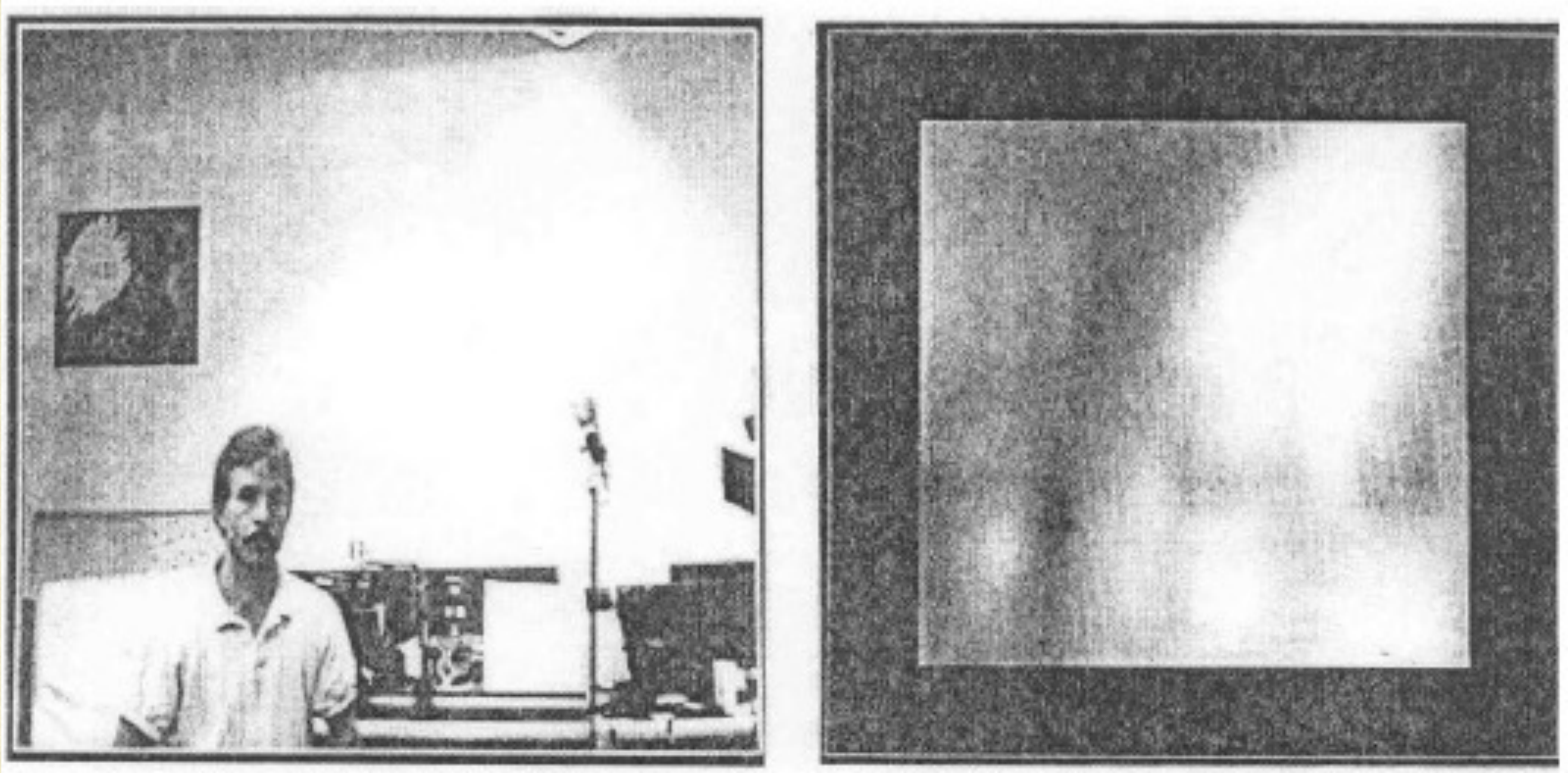
<u>Step 3:</u> compute $e_d = \|\Phi - \hat{\Phi}\|$

<u>Step 4:</u> if $e_d < T_d$, then Γ is a face.

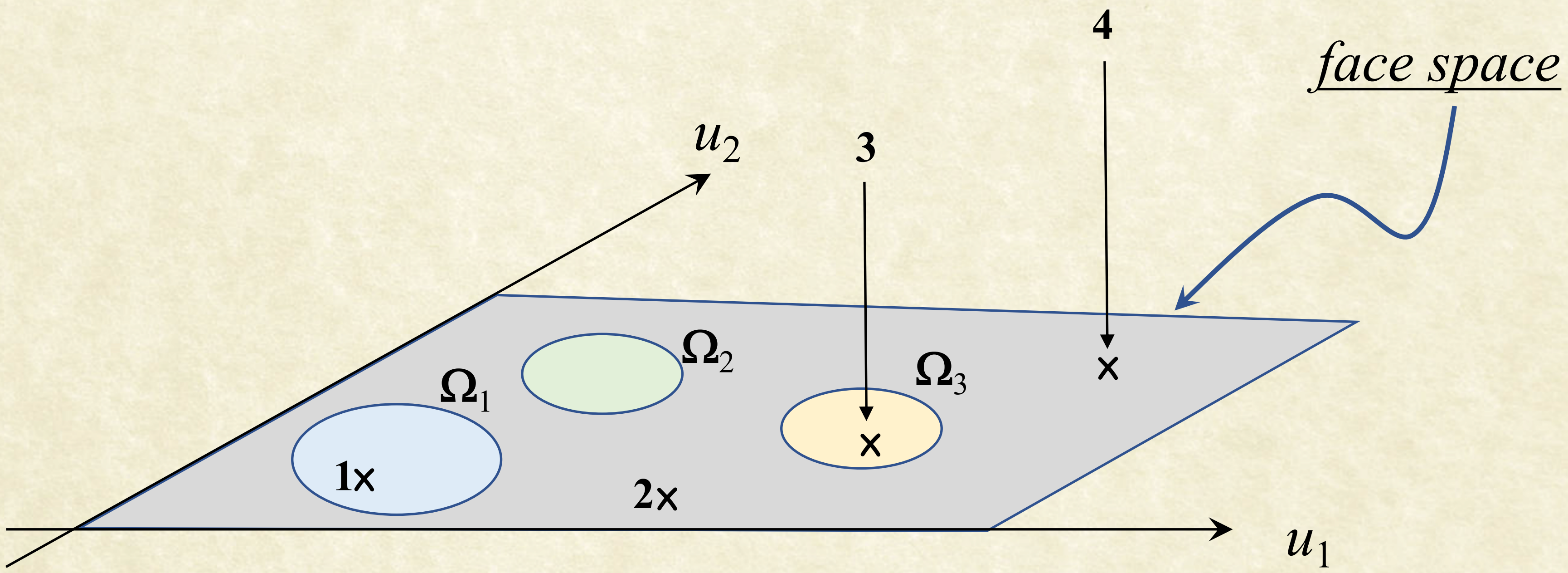
$e_d = \|\Phi - \hat{\Phi}\|$ is called distance from face space (dffs)

Distance from Face Space

Visualize dffs: $e_d = \|\Phi - \hat{\Phi}\|$



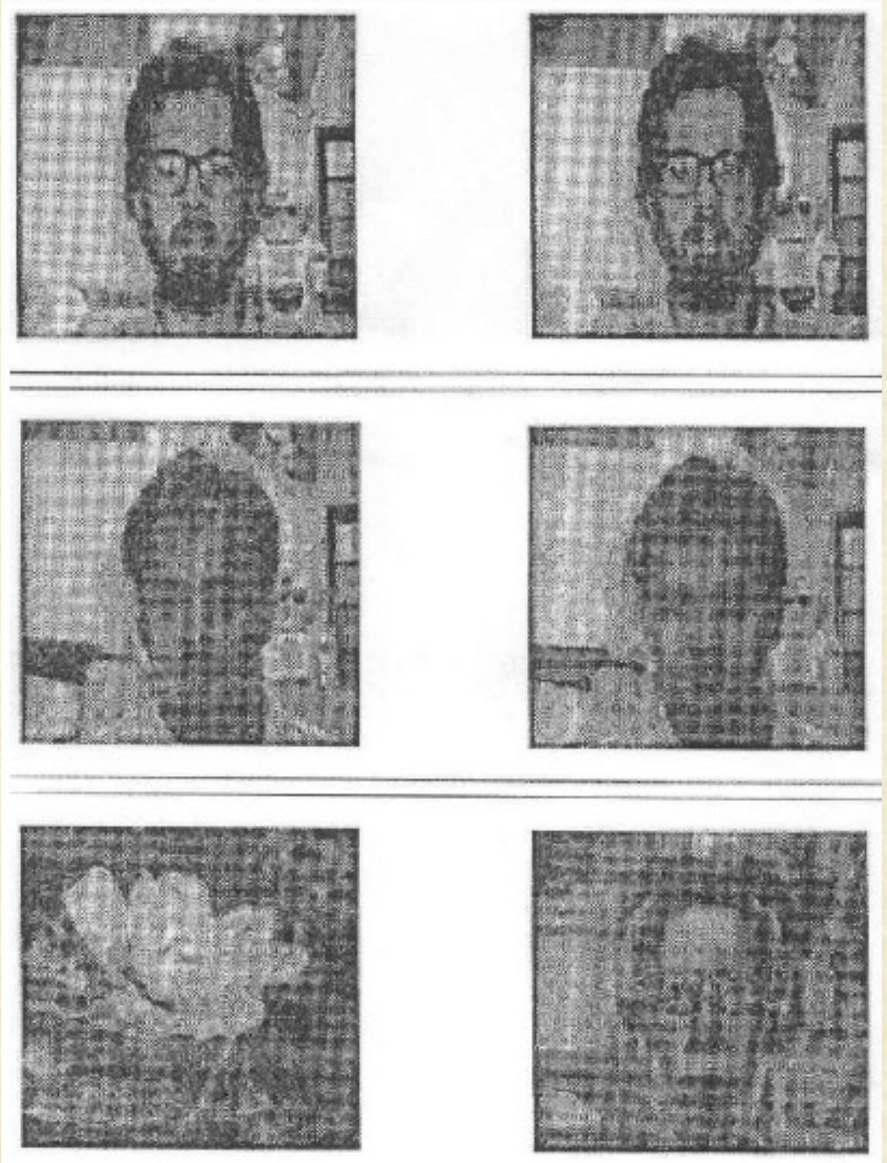
Face Detection using Eigenfaces



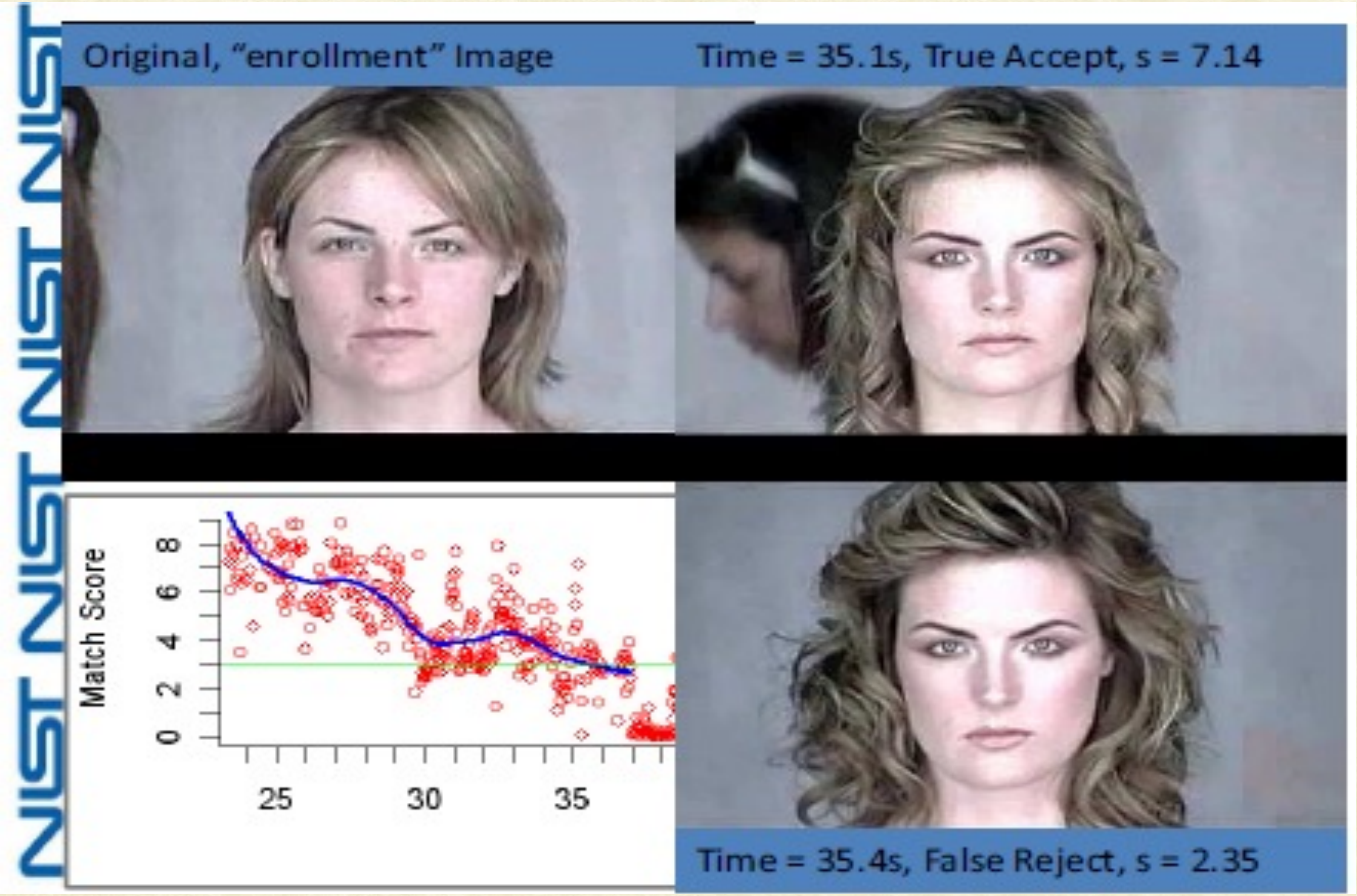
- Case 1: in face space AND close to a given face
- Case 2: in face space but NOT close to any given face
- Case 3: not in face space AND close to a given face
- Case 4: not in face space and NOT close to any given face

Reconstruction from Face Space

- Reconstructed face looks like a face.
- Reconstructed non-face also looks like a face !!
- Robust to partial face occlusion !!



Face Recognition Test: George Quinn (NIST)



Thank You