



EIGENFACES

HYUN SOO PARK

CHALLENGES OF VISUAL RECOGNITION



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- Appearance
 - DOF: texture, illumination, material, shading, ...
- Shape
 - DOF: object category, geometric pose, viewpoint, ...



CHALLENGES OF VISUAL RECOGNITION

- **Appearance**

- DOF: texture, illumination, material, shading, ...

- **Shape**

- DOF: object category, geometric pose, viewpoint, ...



SPACE OF APPEARANCE (FIXED SHAPE)



$$x \in \mathbb{R}^D$$

Template

High dimension (D)

e.g., D: 10,000 = 100 x 100

SPACE OF APPEARANCE (FIXED SHAPE)



Template

$$x \in \mathbb{R}^D$$

High dimension (D)

e.g., D: 10,000 = 100 x 100

Naïve face detection algorithm:



x



x



y

Use NCC or SSD to measure similarity.

maximize $corr(x, y)$

minimize $\|x - y\|^2$

Why not working?

SPACE OF FACE APPEARANCE



SPACE OF FACE APPEARANCE



MISS KOREA CONTESTANTS

Observation: not all pixels are equally informative to detect a face



MISS KOREA CONTESTANTS

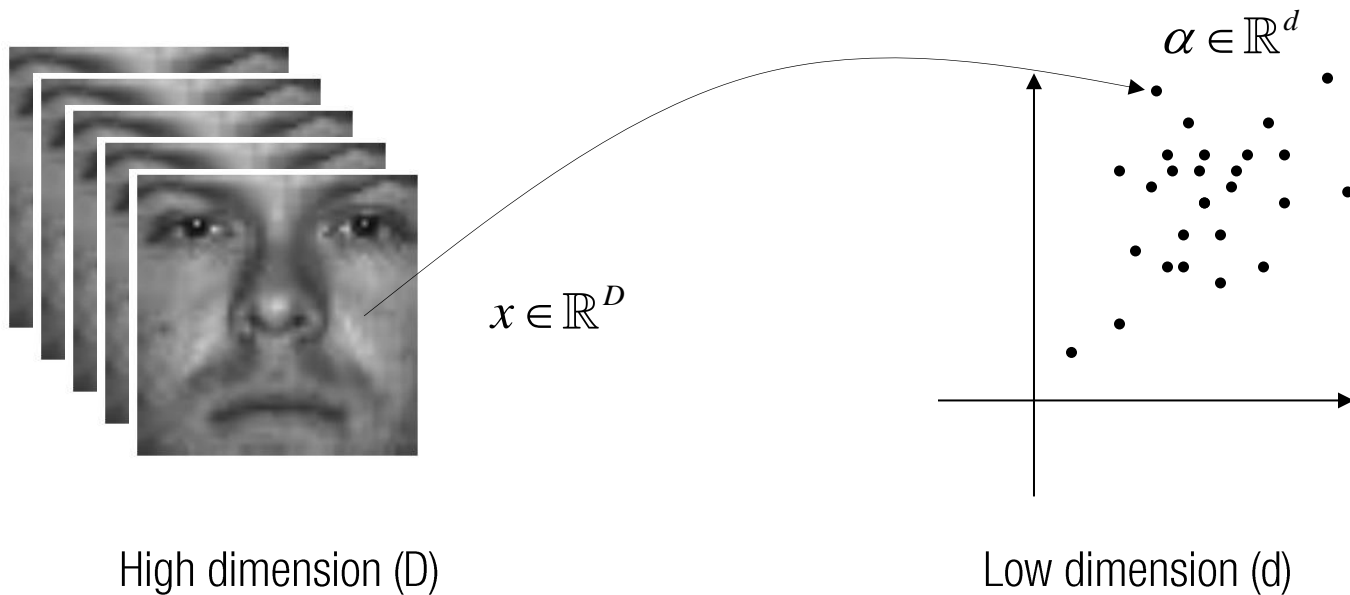
Observation: not all pixels are equally informative to detect a face




Average image

STRUCTURED APPEARANCE

Idea: face images are highly correlated and can be represented in a low-dimensional subspace.



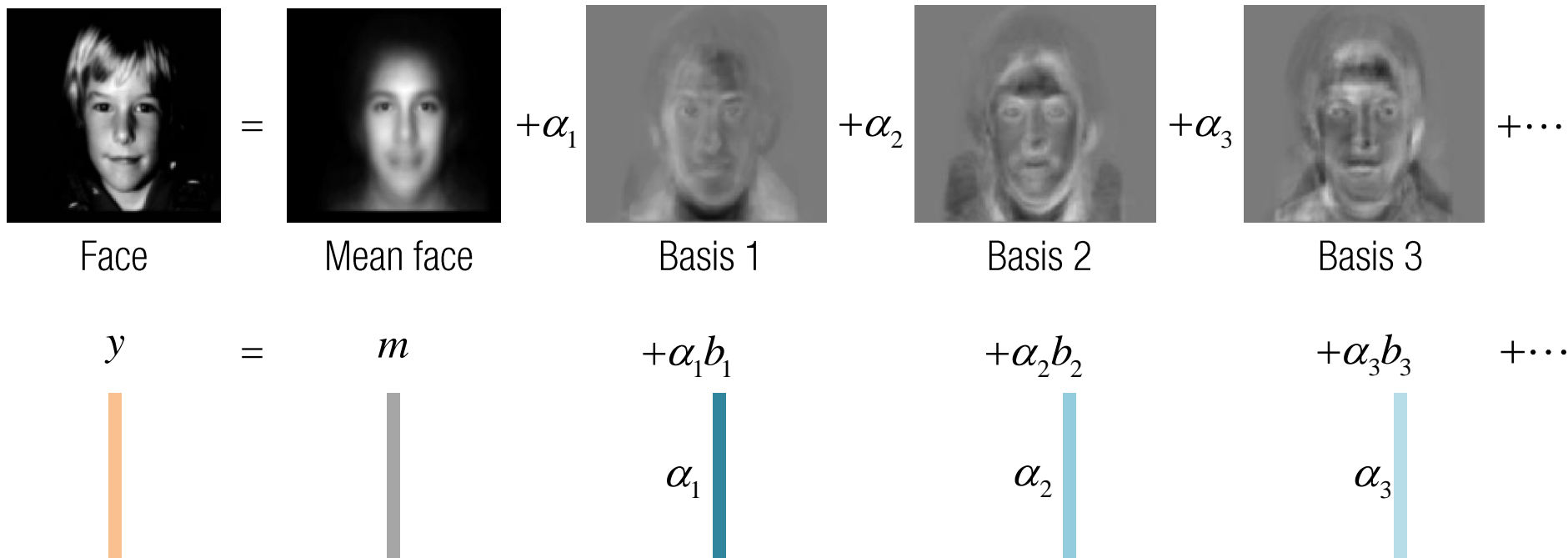
LINEAR BASIS



Face = Mean face + α_1 Basis 1 + α_2 Basis 2 + α_3 Basis 3 + ...

$y = m + \alpha_1 b_1 + \alpha_2 b_2 + \alpha_3 b_3 + \dots$

LINEAR BASIS



LINEAR BASIS



Face

Mean face

Basis 1

Basis 2

Basis 3

$$y \approx m + B\alpha$$

y \approx m + B α

The matrix B is represented by vertical bars of varying shades of blue, and the vector α is represented by a purple box containing $\alpha_1, \dots, \alpha_d$.

RECONSTRUCTION FROM LINEAR BASIS



Face

Mean face

Basis 1

Basis 2

Basis 3

$$y = m + \alpha_1 b_1 + \alpha_2 b_2 + \alpha_3 b_3 + \dots$$

$$y \approx m + \begin{bmatrix} | & | & | & \dots \\ \text{Basis} & & & \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_d \end{bmatrix}$$

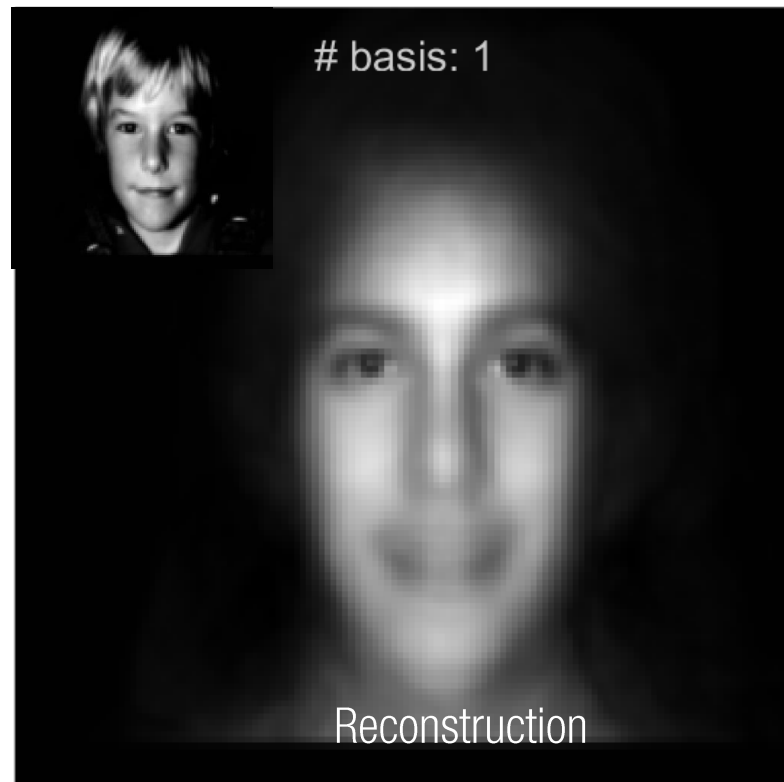
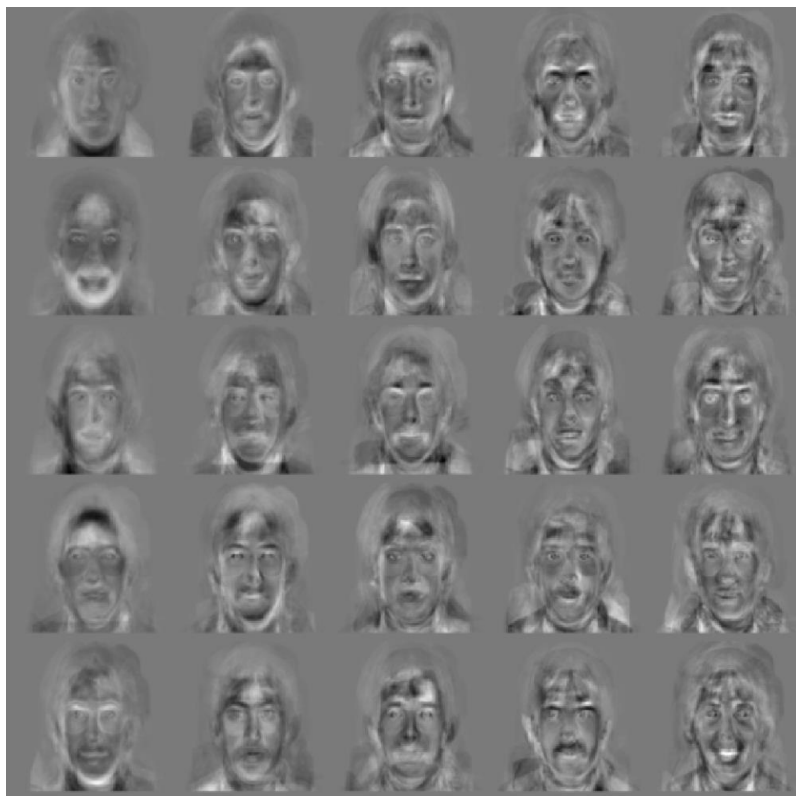
$$y \approx m + B \alpha$$

Mean
Basis
Coefficient

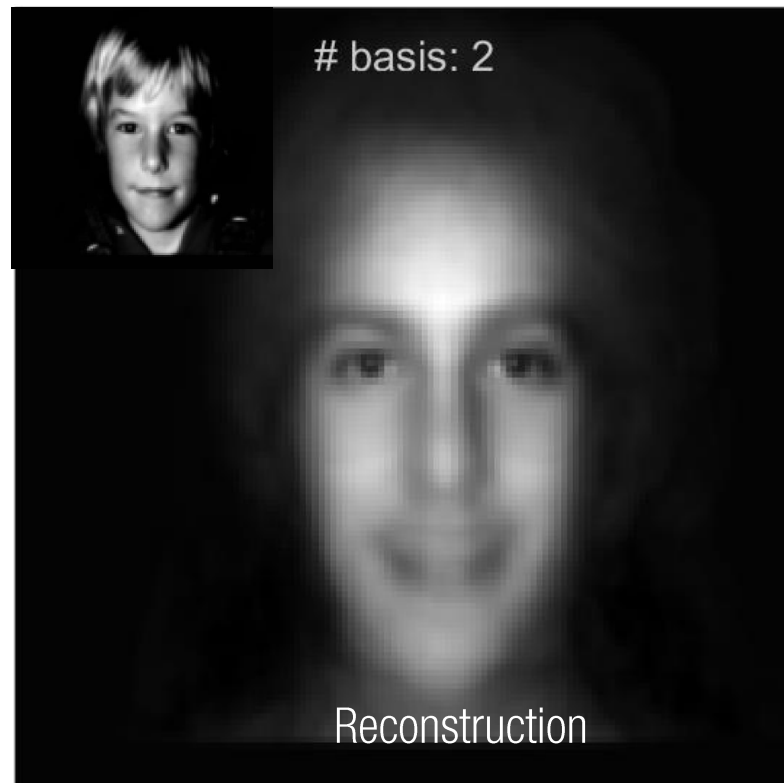
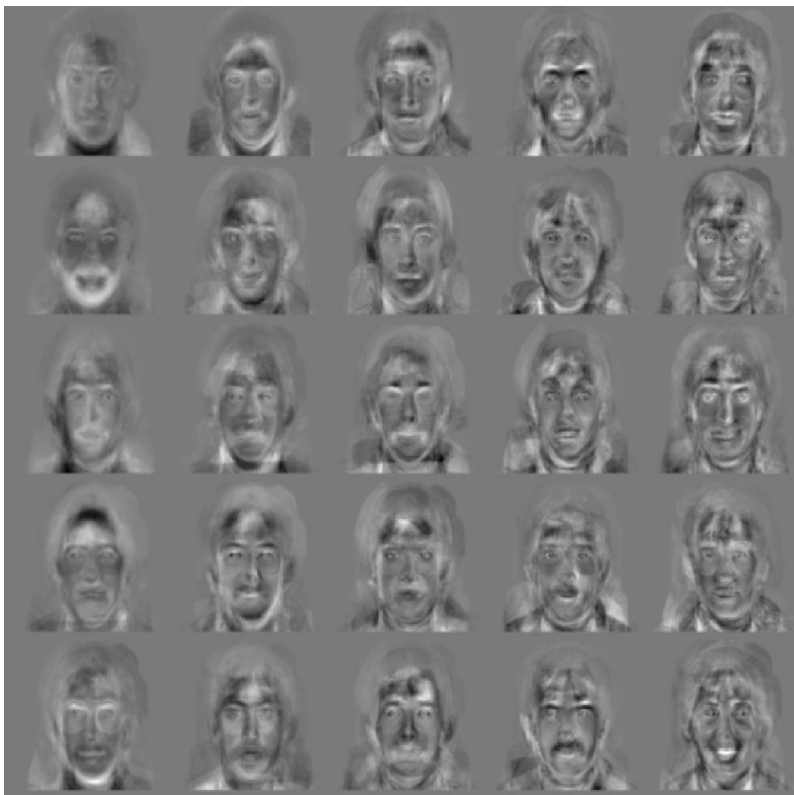
$$\alpha^* = \underset{\alpha}{\text{minimize}} \|y - m - B\alpha\|^2$$

Cf) $\text{minimize} \|x - y\|^2$
 Template matching

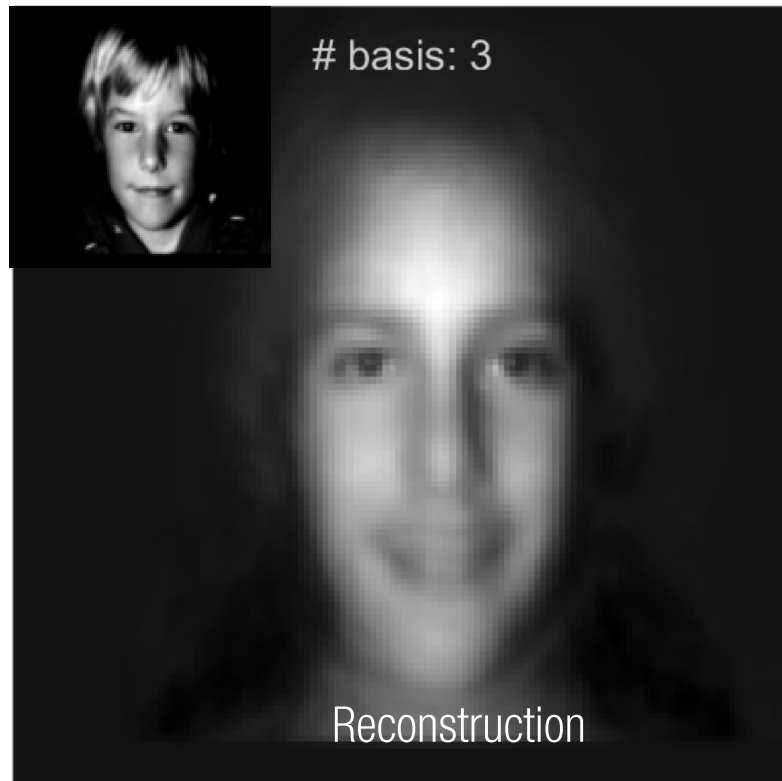
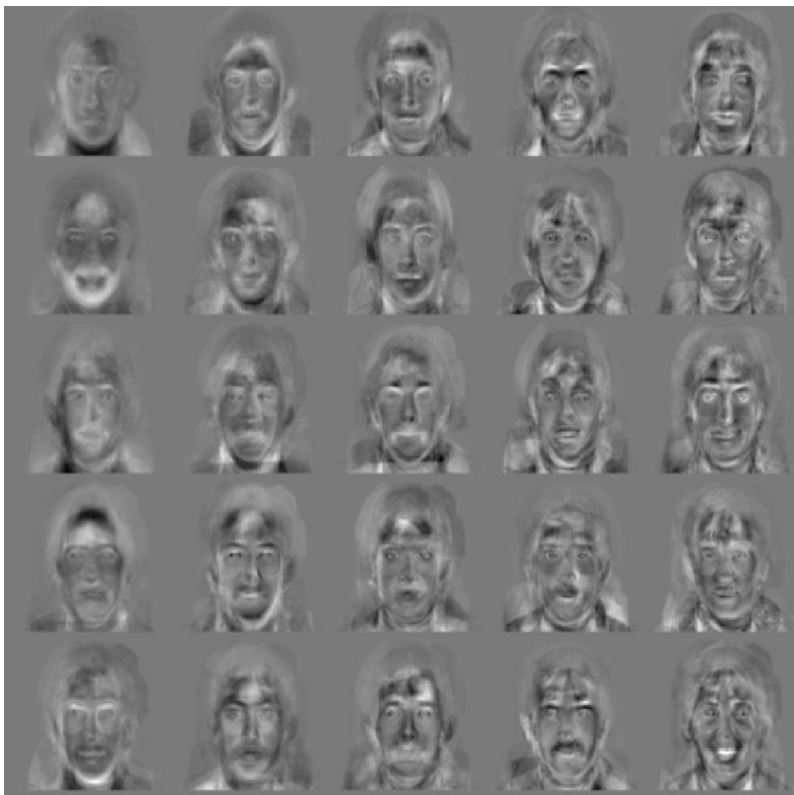
RECONSTRUCTION EXPRESSIBILITY



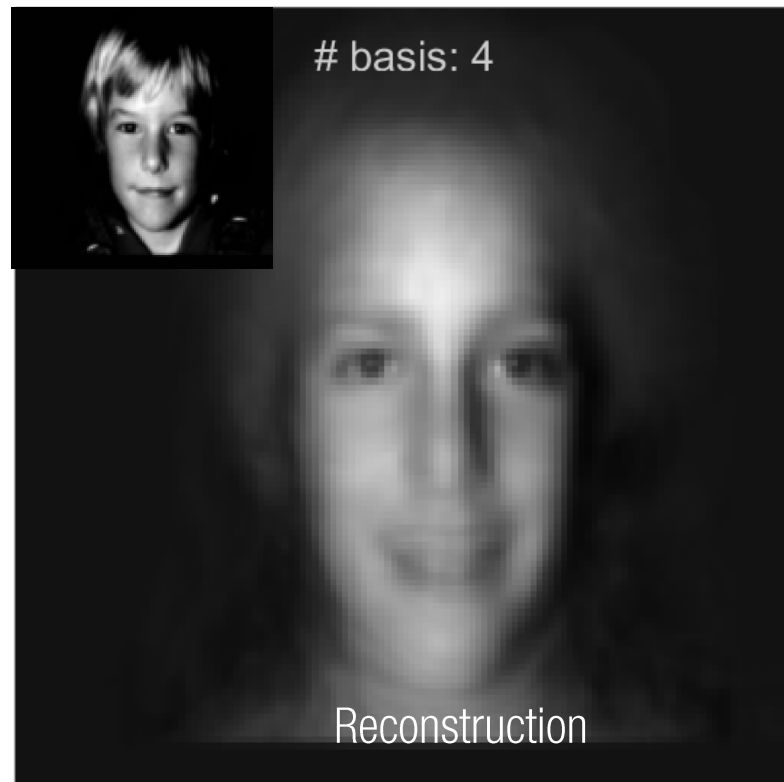
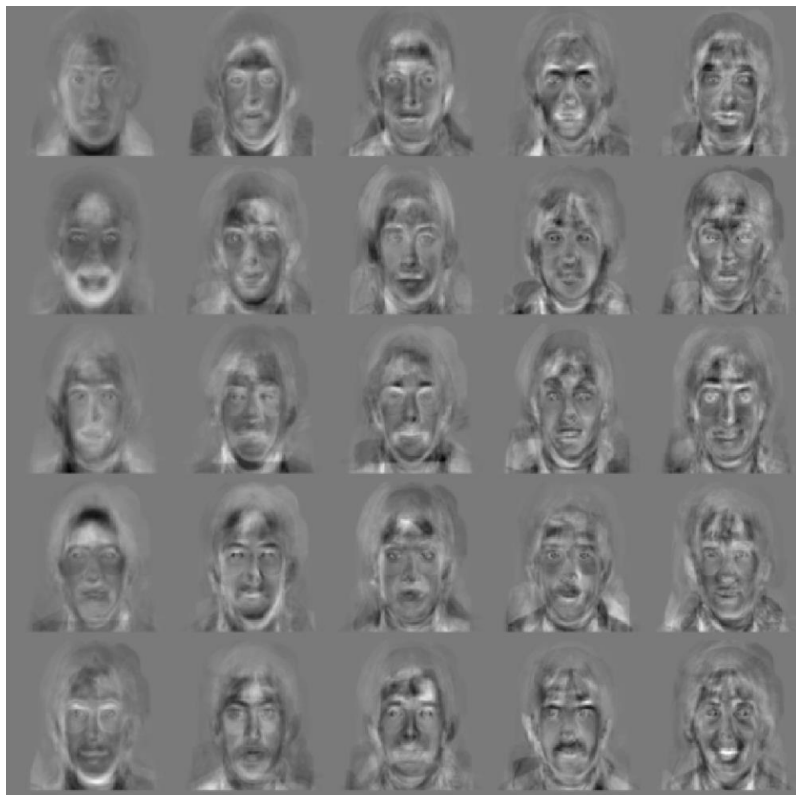
RECONSTRUCTION EXPRESSIBILITY



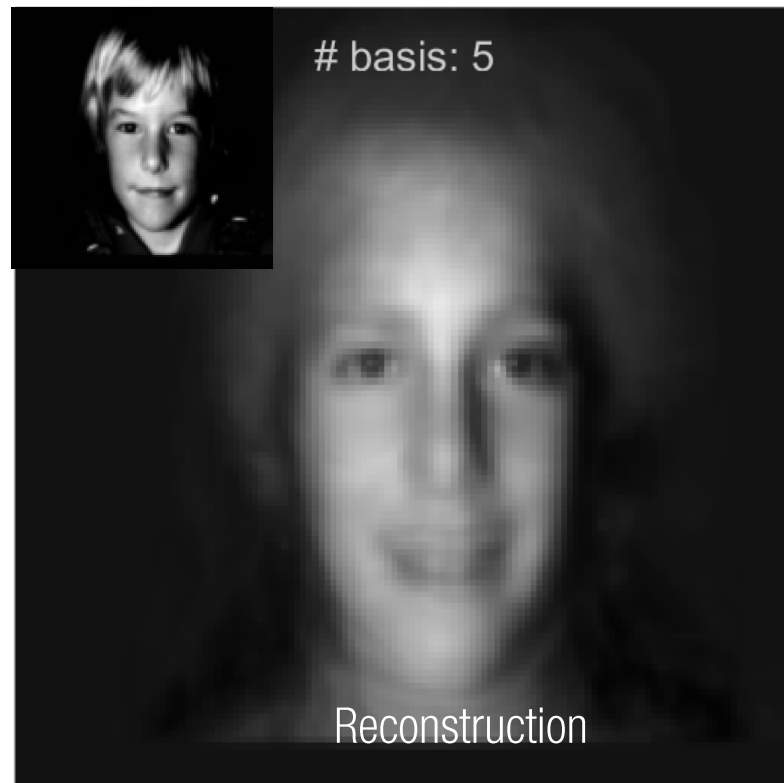
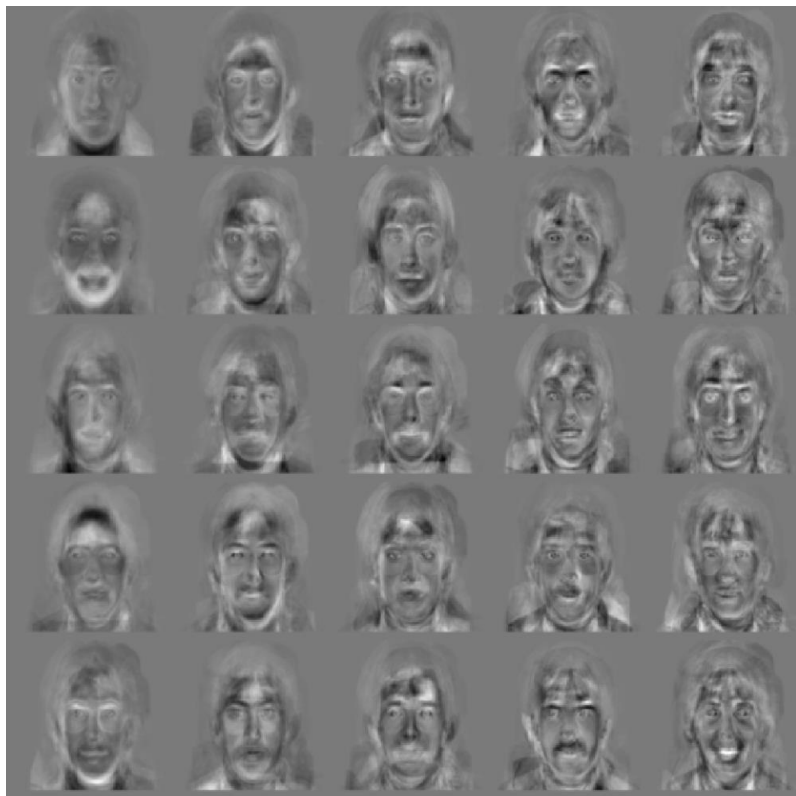
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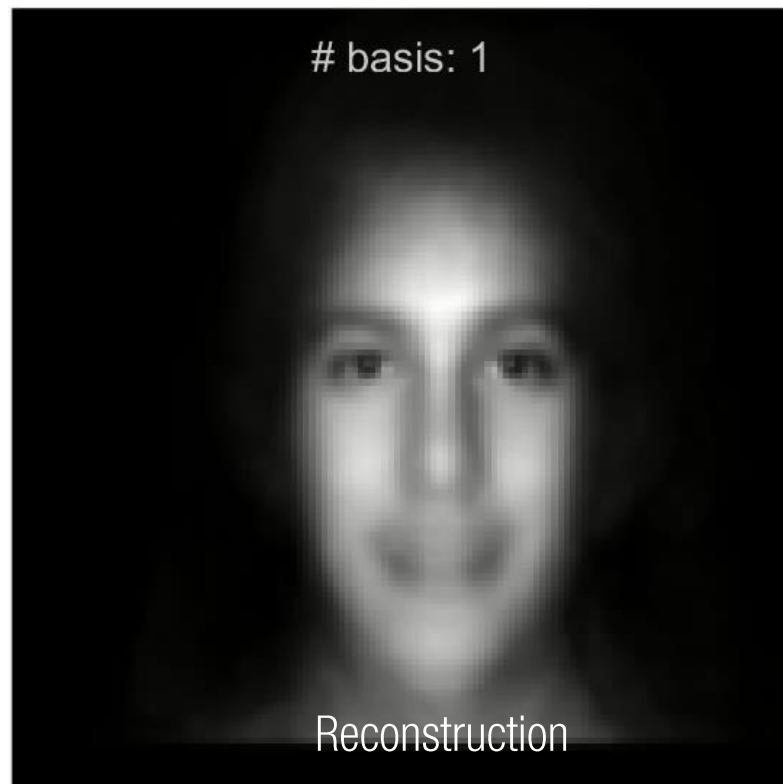
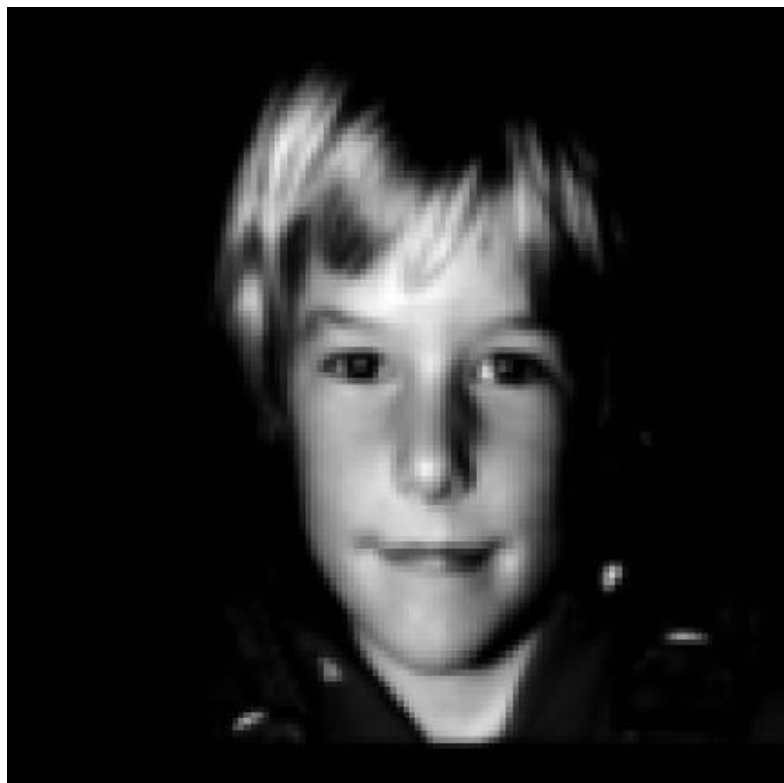
RECONSTRUCTION EXPRESSIBILITY



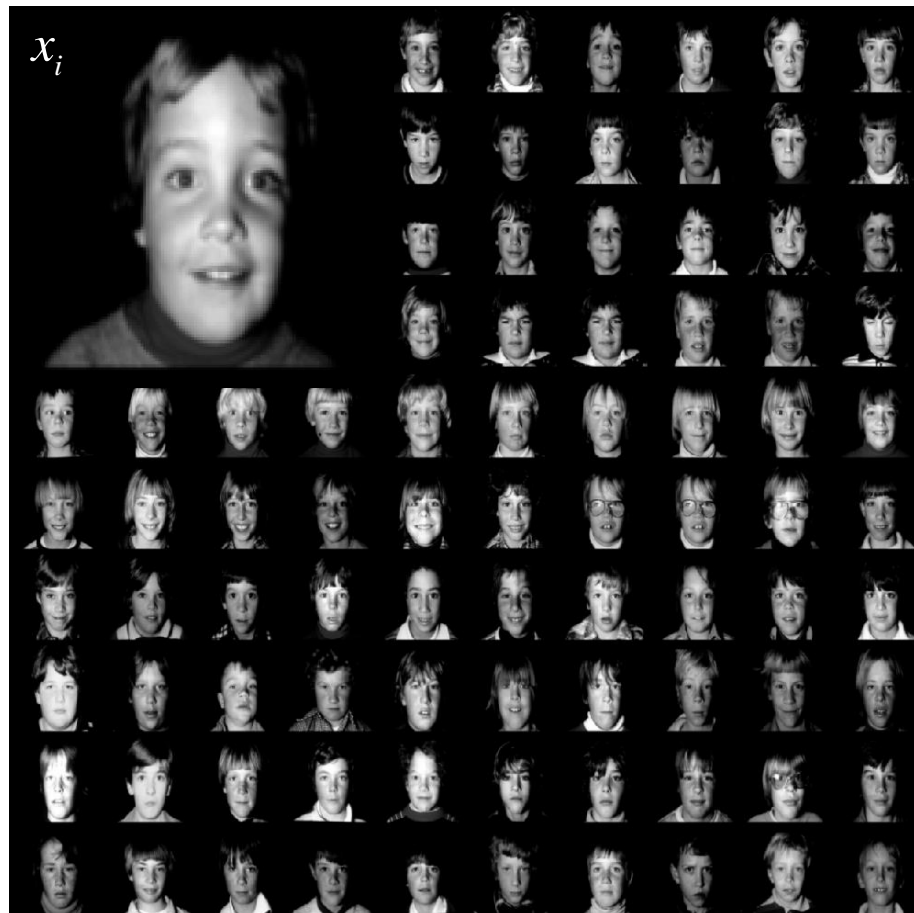
RECONSTRUCTION EXPRESSIBILITY



RECONSTRUCTION EXPRESSIBILITY

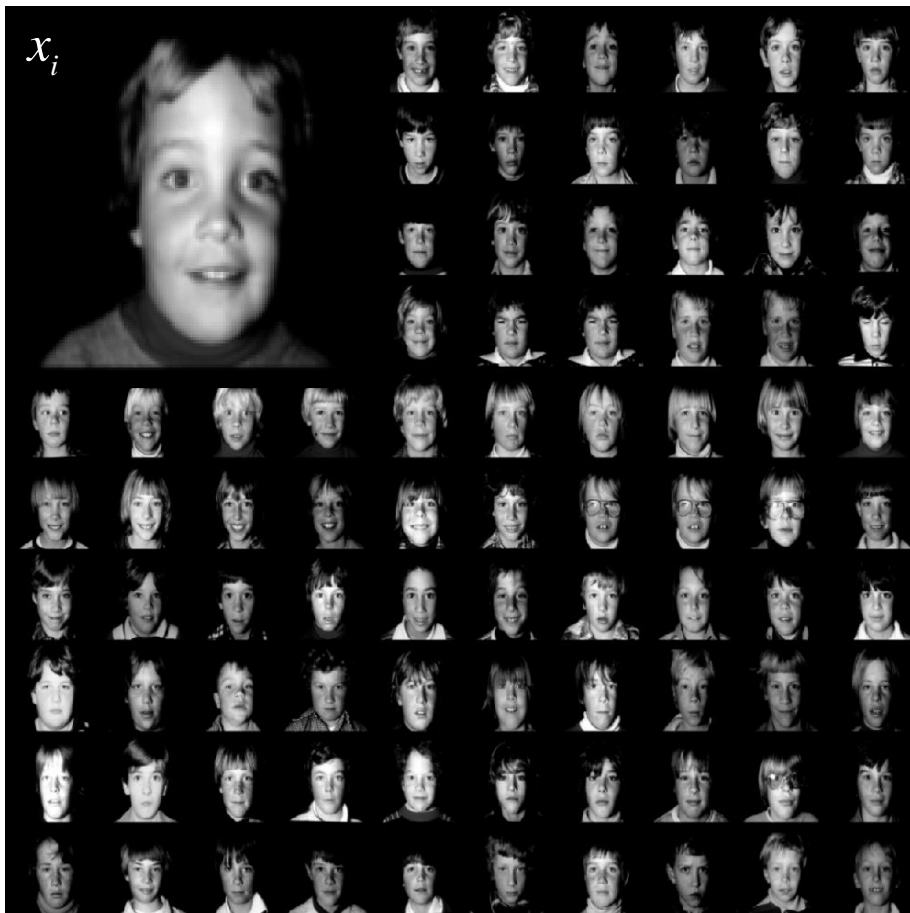


HOW TO COMPUTE MEAN AND BASIS FROM DATABASE?



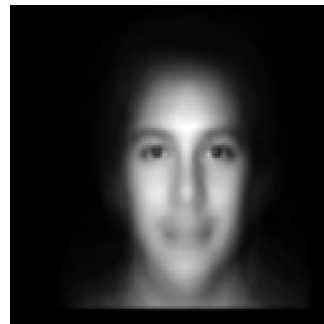
$$m^*, B^*, \alpha^* = \underset{m, B, \alpha}{\text{minimize}} \|y - m - B\alpha\|^2$$

HOW TO COMPUTE MEAN?

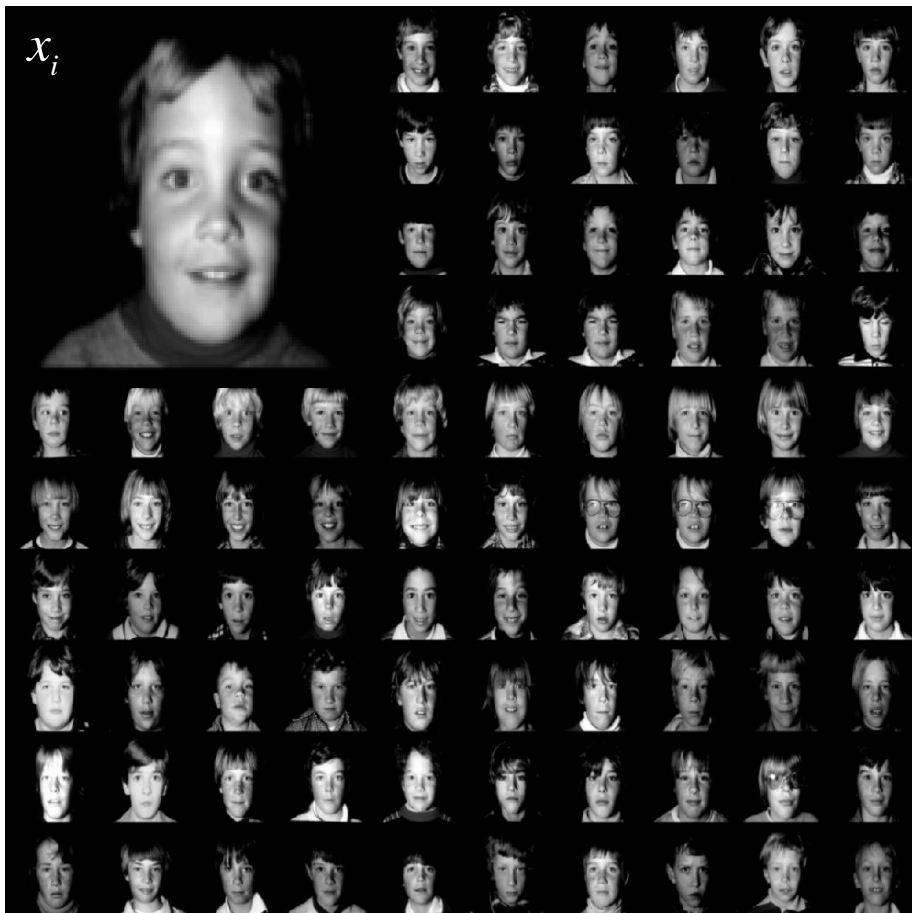


$$m^*, B^*, \alpha^* = \underset{m, B, \alpha}{\text{minimize}} \|y - m - B\alpha\|^2$$

$$m = \frac{1}{n} \sum_i^n x_i$$

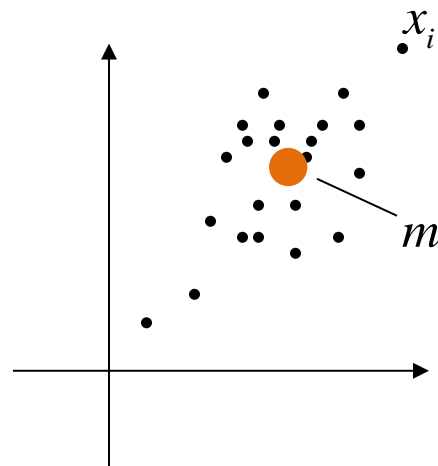
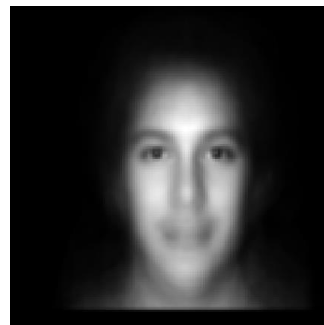


HOW TO COMPUTE MEAN?



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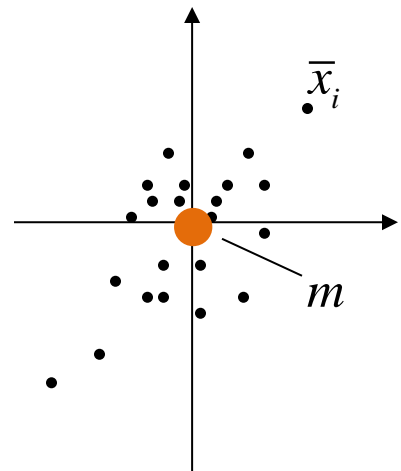


MEAN SUBTRACTION



$$m^*, B^*, \alpha^* = \underset{m, B, \alpha}{\text{minimize}} \|y - m - B\alpha\|^2$$

$$m = \frac{1}{n} \sum_i^n x_i$$



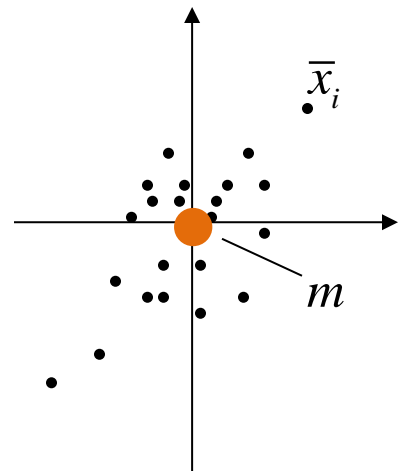
$$\bar{x}_i = x_i - m$$

HOW TO COMPUTER BASIS?



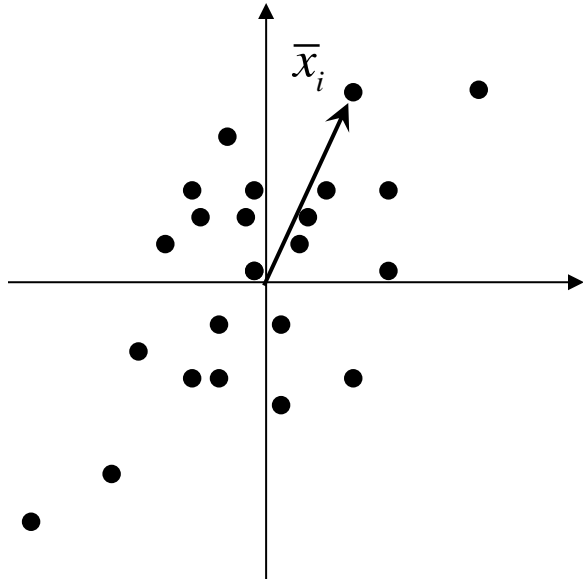
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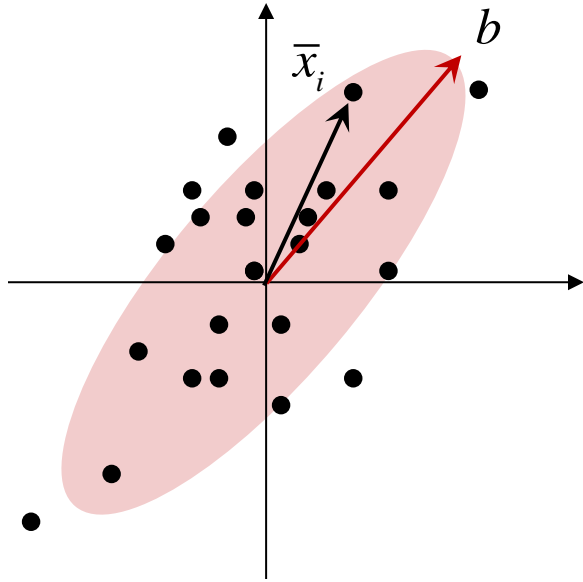


$$\bar{x}_i = x_i - m$$

PRINCIPAL AXIS

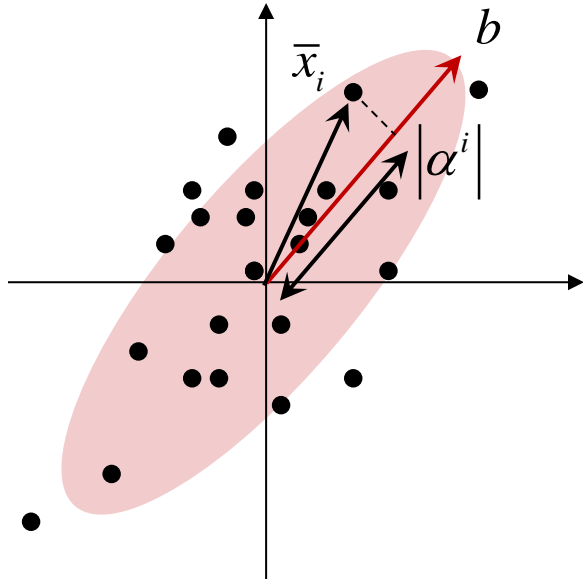


PRINCIPAL AXIS



Basis is the axis that represents the maximum data covariance.

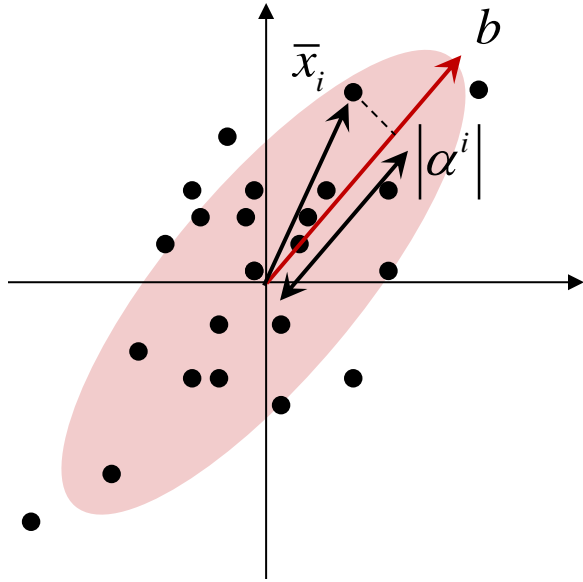
PRINCIPAL AXIS



Basis is the axis that represents the maximum data covariance.

Coefficient $\alpha^i = \frac{b \cdot \bar{x}_i}{\|b\|}$

PRINCIPAL AXIS

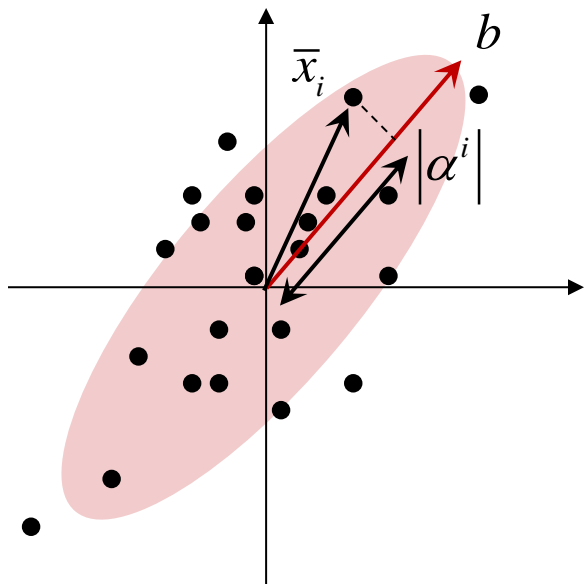


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$$b^* = \underset{b}{\text{maximize}} \sum_{i=1}^n (\alpha^i)^2$$

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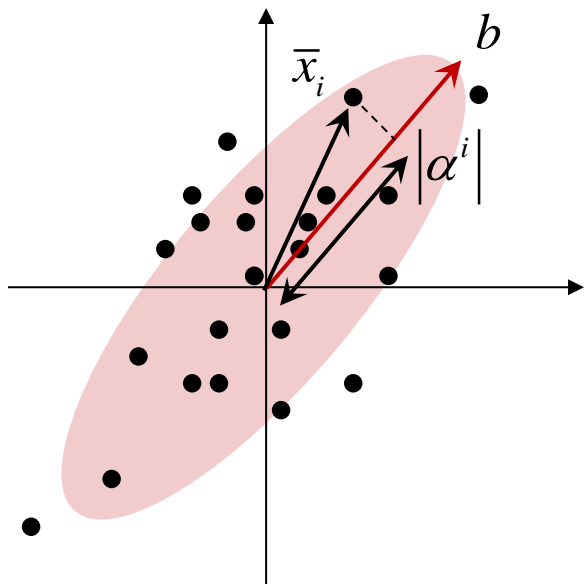


Basis is the axis that represents the maximum data covariance.

$$\text{Coefficient } \alpha^i = \frac{b \cdot \bar{x}_i}{\|b\|}$$

$$\begin{aligned} b^* &= \underset{b}{\text{maximize}} \sum_{i=1}^n (\alpha^i)^2 \\ &= \underset{b}{\text{maximize}} \sum_{i=1}^n \left(\frac{b \cdot \bar{x}_i}{\|b\|} \right)^2 \end{aligned}$$

PRINCIPAL AXIS



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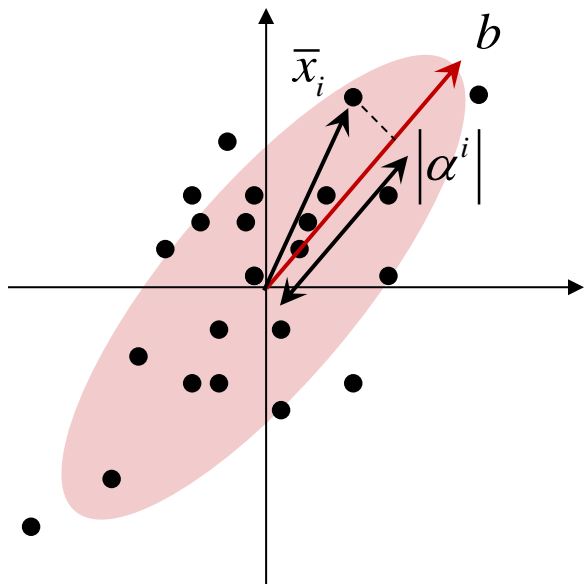
$$b^* = \underset{b}{\text{maximize}} \sum_{i=1}^n (\alpha^i)^2$$

$$= \underset{b}{\text{maximize}} \sum_{i=1}^n \left(\frac{b \cdot \bar{x}_i}{\|b\|} \right)^2$$

$$= \underset{b}{\text{maximize}} b^T \underbrace{X^T X}_{\text{Covariance matrix}} b$$

$$\text{where } x = \begin{bmatrix} x_1^T \\ \vdots \\ x_n^T \end{bmatrix}$$

PRINCIPAL AXIS



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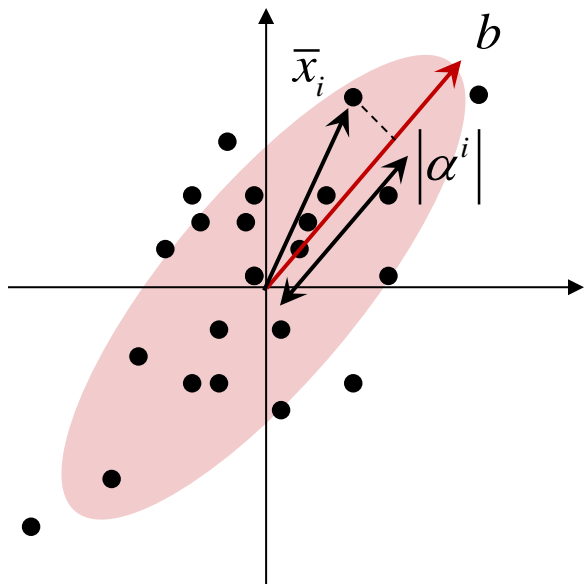
$$= \underset{b}{\text{maximize}} \sum_{i=1}^n \left(\frac{b \cdot \bar{x}_i}{\|b\|} \right)^2$$

$$= \underset{b}{\text{maximize}} b^T \underbrace{X^T X}_{\text{Covariance matrix}} b$$

Covariance matrix

Solution is the eigenvector corresponding to the largest eigenvalue: $b^* = \lambda_{\max}(X^T X)$

PRINCIPAL AXIS



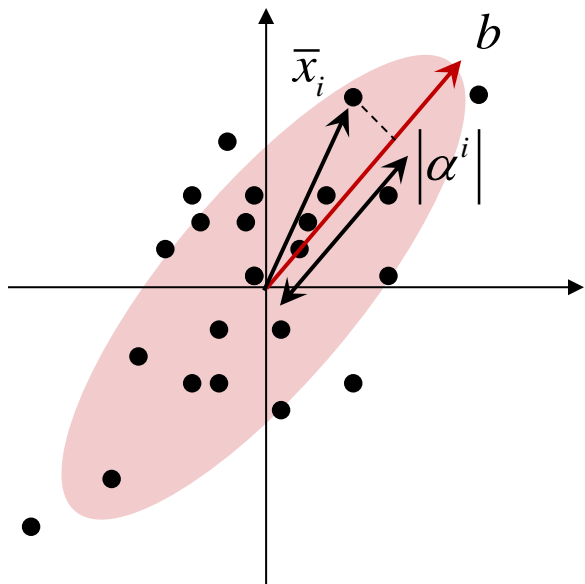
Basis is the axis that represents the maximum data covariance.

Coefficient $\alpha^i = \frac{b \cdot \bar{x}_i}{\|b\|}$

$$\begin{bmatrix} \alpha^1 \\ \vdots \\ \alpha^n \end{bmatrix}_{n \times 1} = \begin{bmatrix} \bar{x}_1^T \\ \vdots \\ \bar{x}_n^T \end{bmatrix}_{n \times D} \begin{bmatrix} b \end{bmatrix}_{D \times 1}$$



PRINCIPAL AXES



Basis is the axis that represents the maximum data covariance.

Coefficient $\alpha_j^i = \frac{b_j \cdot \bar{x}_i}{\|b_j\|}$

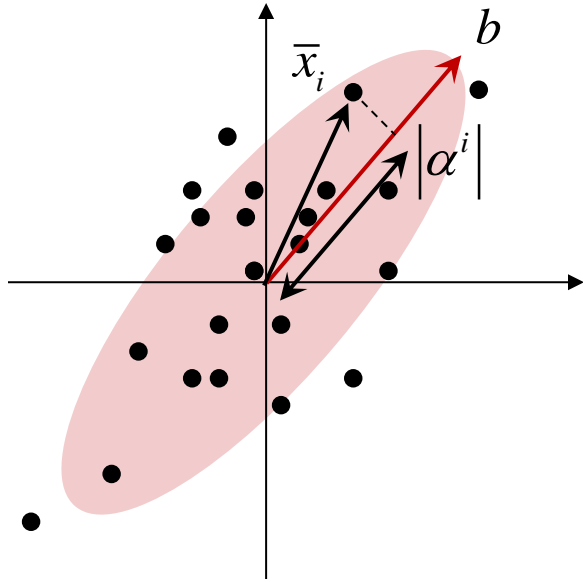
Orthogonal principal axes:
first d largest eigenvectors

$$\begin{bmatrix} \alpha_1^1 & \dots & \alpha_d^1 \\ \vdots & & \vdots \\ \alpha_n^1 & \dots & \alpha_n^d \end{bmatrix}_{n \times d} = \begin{bmatrix} \bar{x}_1^T \\ \vdots \\ \bar{x}_n^T \end{bmatrix}_{n \times D} \begin{bmatrix} b_1 & \dots & b_d \end{bmatrix}_{D \times d}$$

$$d \ll D$$

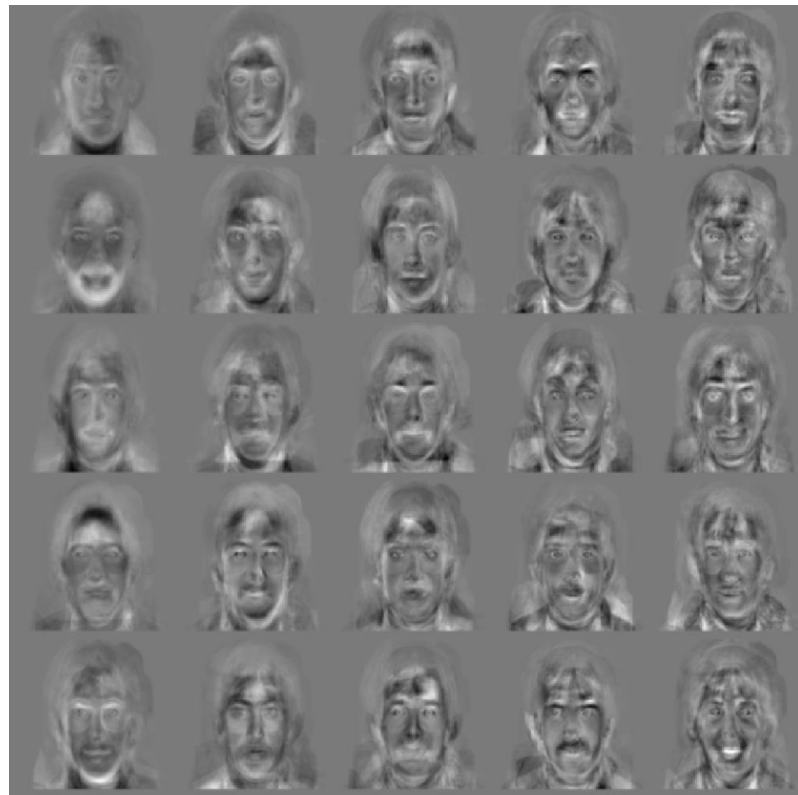


PCA: DIMENSIONAL REDUCTION



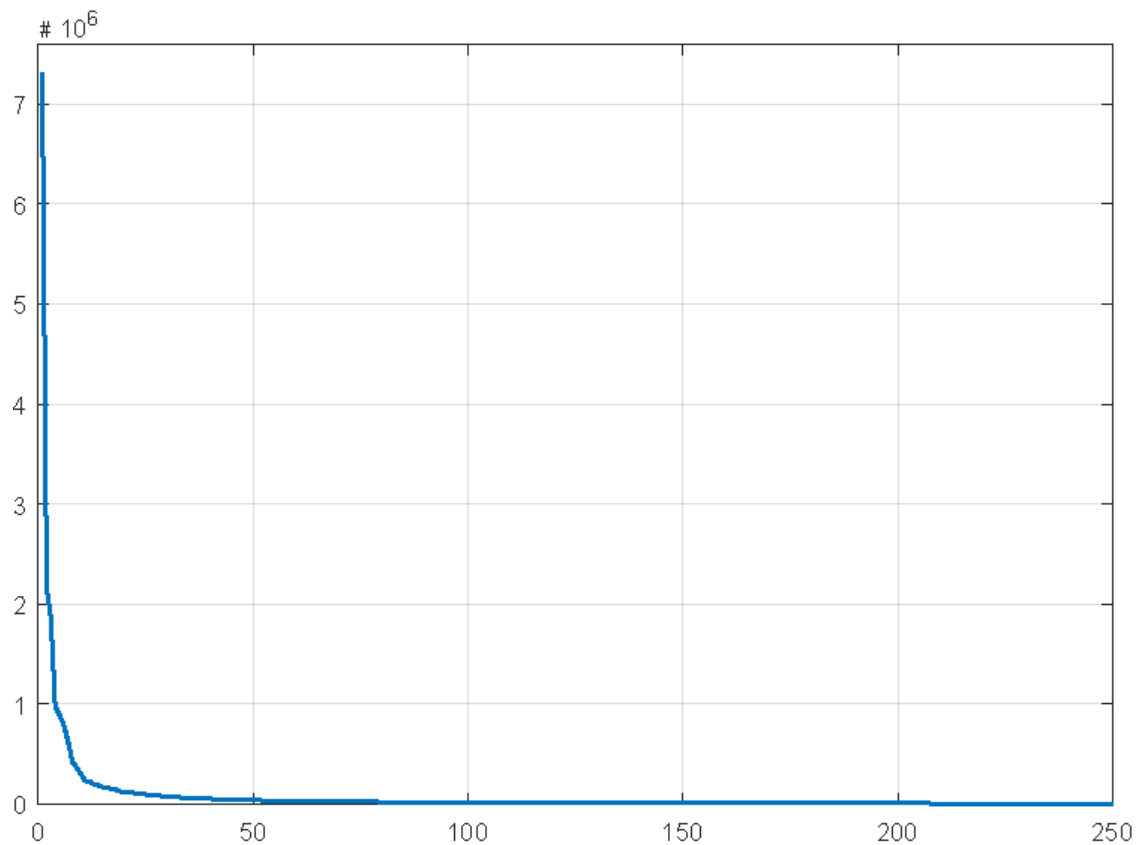
$$\begin{array}{ccc} \boxed{A} & = & \boxed{X} \boxed{B} \\ \text{nxd} & & \text{nxD} \quad \text{Dxd} \\ d \ll D & & \end{array}$$

HOW TO COMPUTE BASIS?

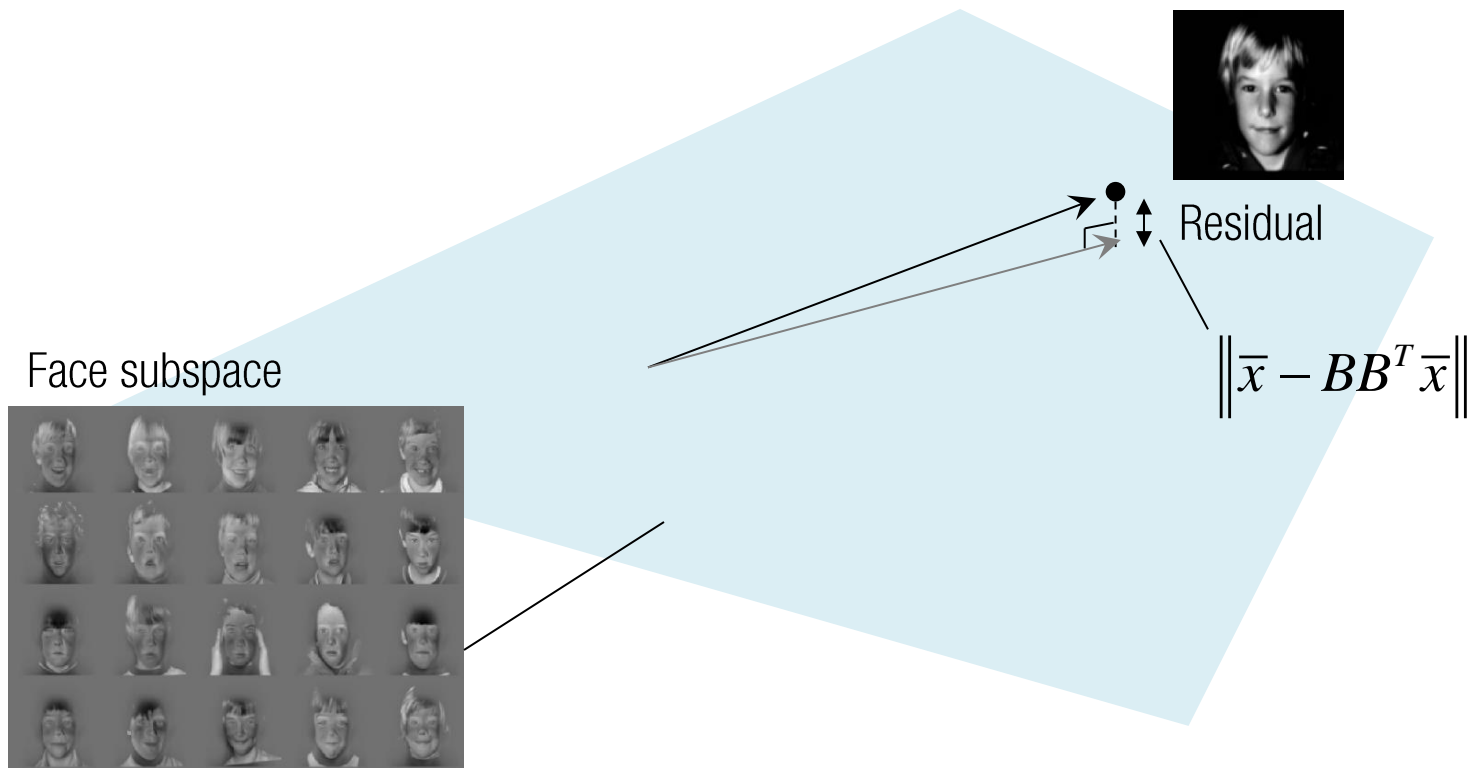


Set of basis vectors

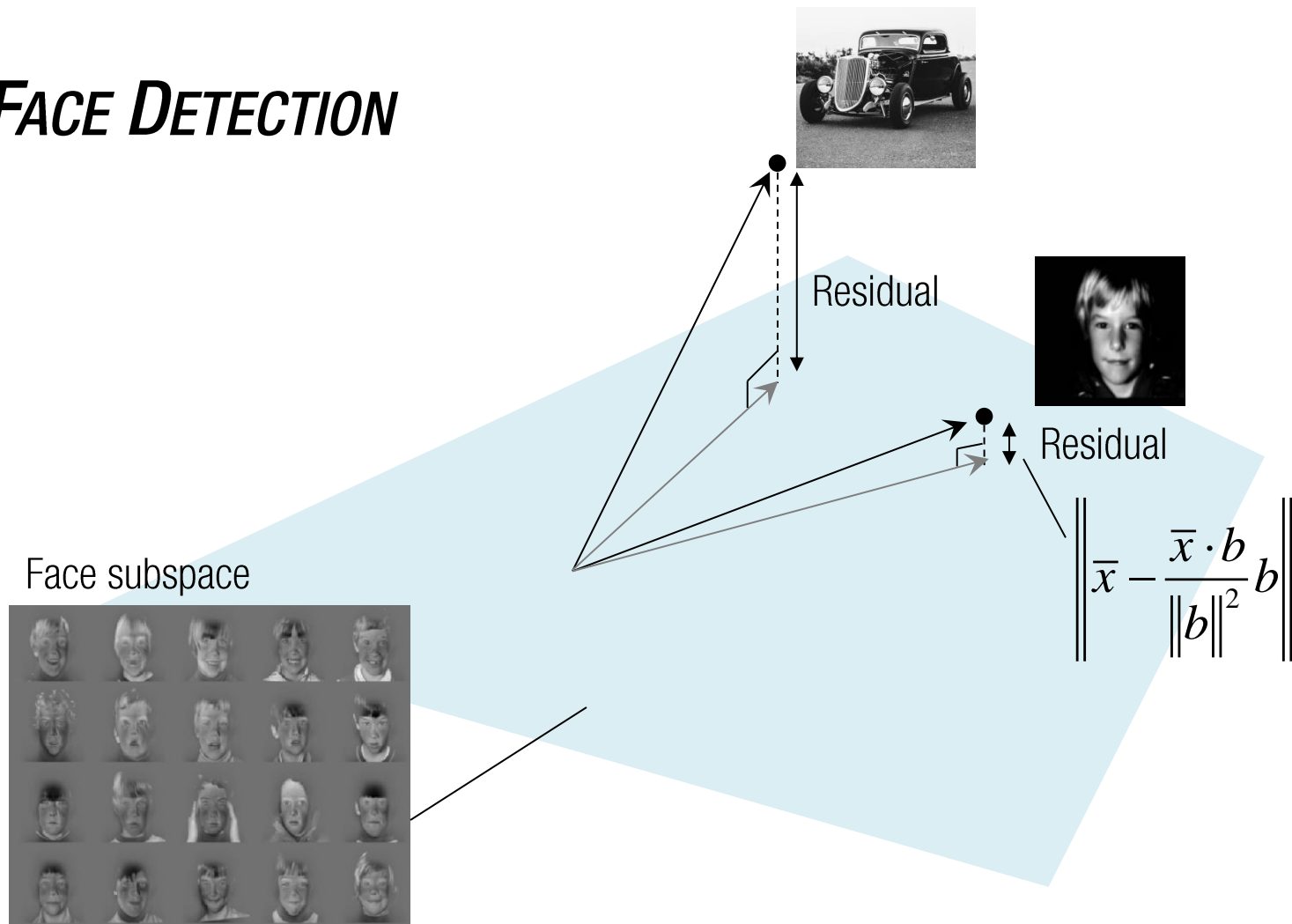
HOW TO CHOOSE # OF BASIS VECTORS?



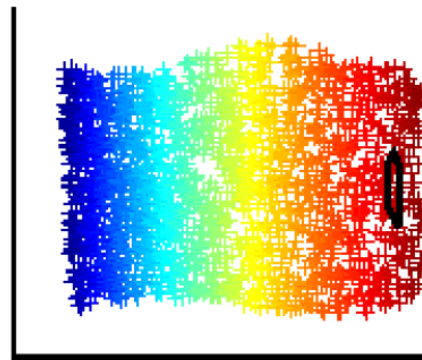
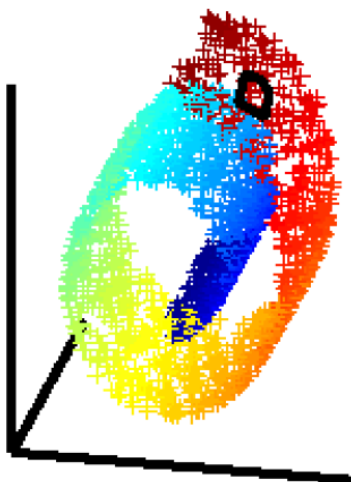
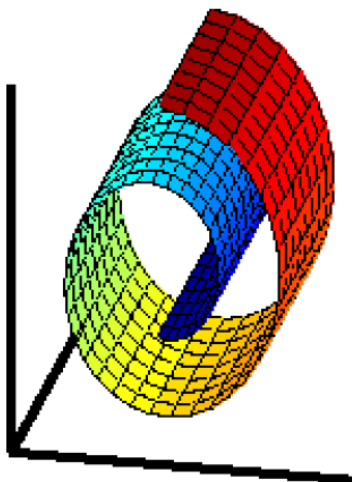
FACE DETECTION



FACE DETECTION



LIMITATION



Object distribution does not follow Gaussian!

<https://www.youtube.com/watch?v=J0arU2PAMIs>