

# 3D Scanning & Motion Capture

## Parametric Face Models

Prof. Dr. Nießner



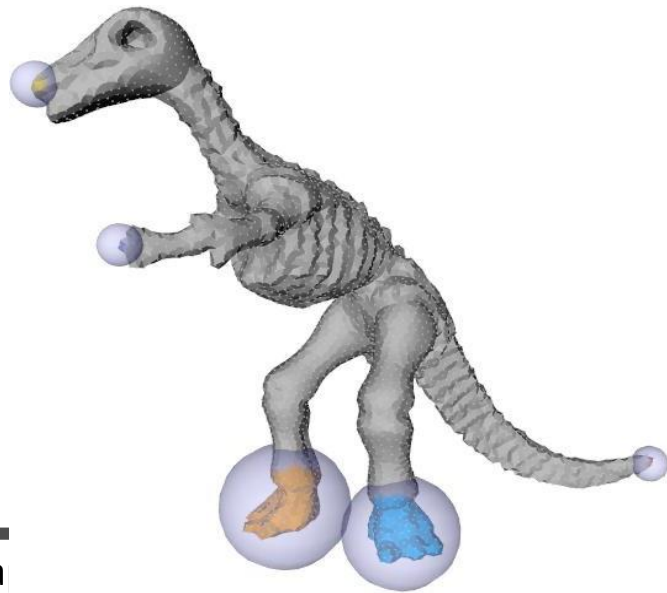
# As-Rigid-as-Possible Deformation

- One rotation matrix per fan; sum up deviations from rigidity

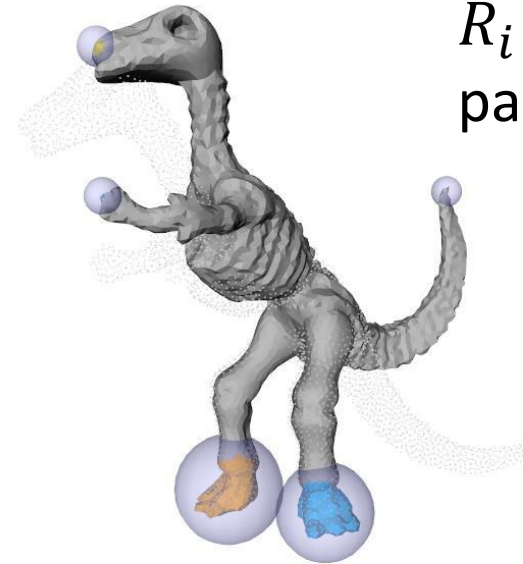
- $E_{ARAP}(\mathbf{R}, \mathbf{V}) = \sum_i \sum_{j \in \mathcal{N}(i)} \left\| (v_i - v_j) - R_i(v'_i - v'_j) \right\|_2^2$

- $E_{fit}(\mathbf{V}) = \sum_{i \in \mathcal{C}} \left\| v'_i - v_i \right\|_2^2$

$R_i$  is rotation matrix and  
parametrized by Euler angles  
 $\alpha, \beta, \gamma$



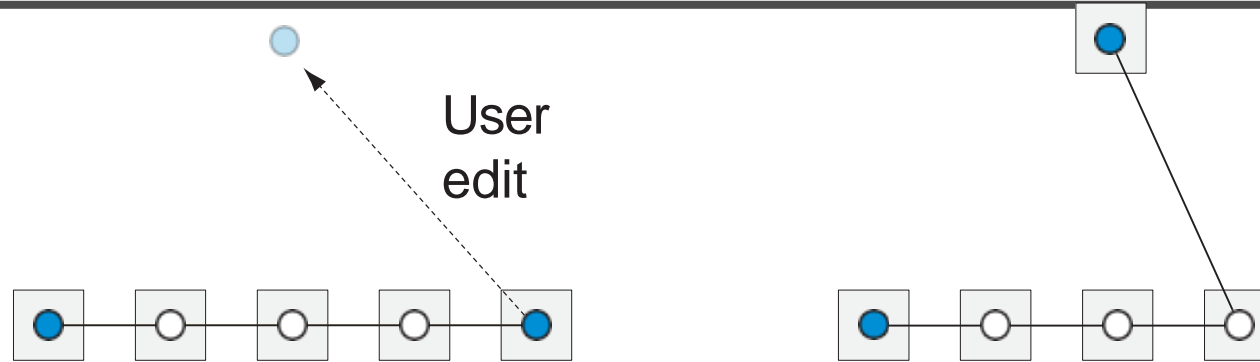
Initial mesh  $V'$



Deformed mesh  $V$

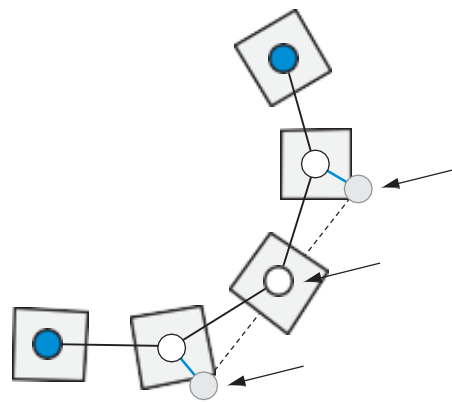
[Sorkine et al. 08]

# Embedded Deformation

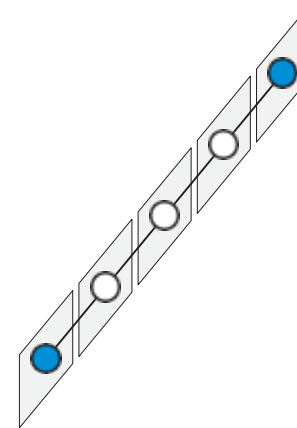


$$E_{ED}(\mathbf{M}, \mathbf{V}) = \sum_i \sum_{j \in \mathcal{N}(i)} \left\| (v_i - v_j) - M_i(v'_i - v'_j) \right\|_2^2$$

$E_{\text{con}}$

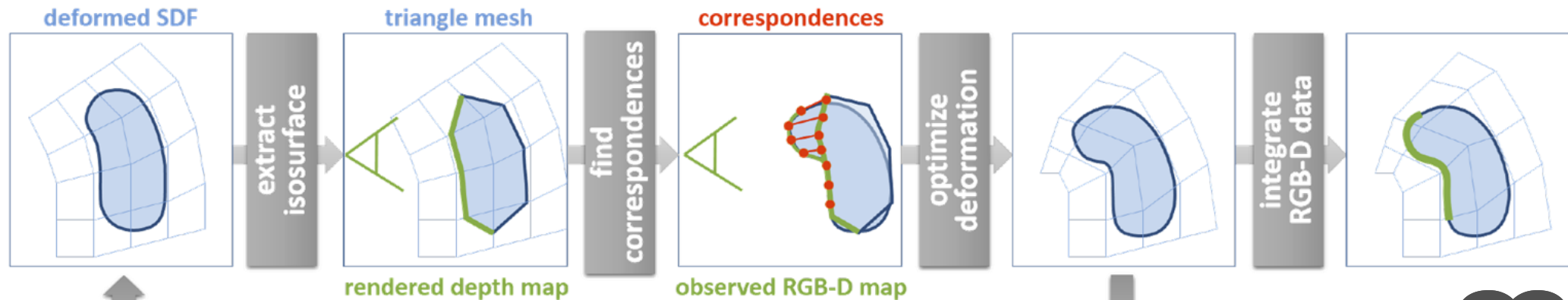
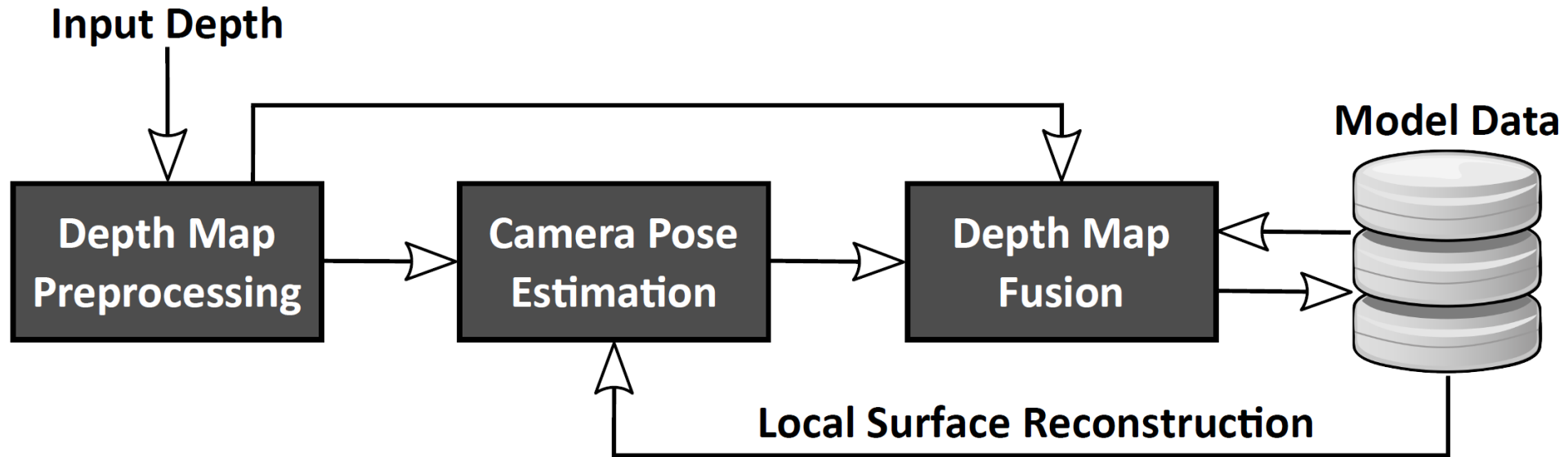


$E_{\text{con}} + E_{\text{reg}} + E_{\text{rot}}$



$E_{\text{con}} + E_{\text{reg}}$

# Rigid vs Non-Rigid Reconstruction



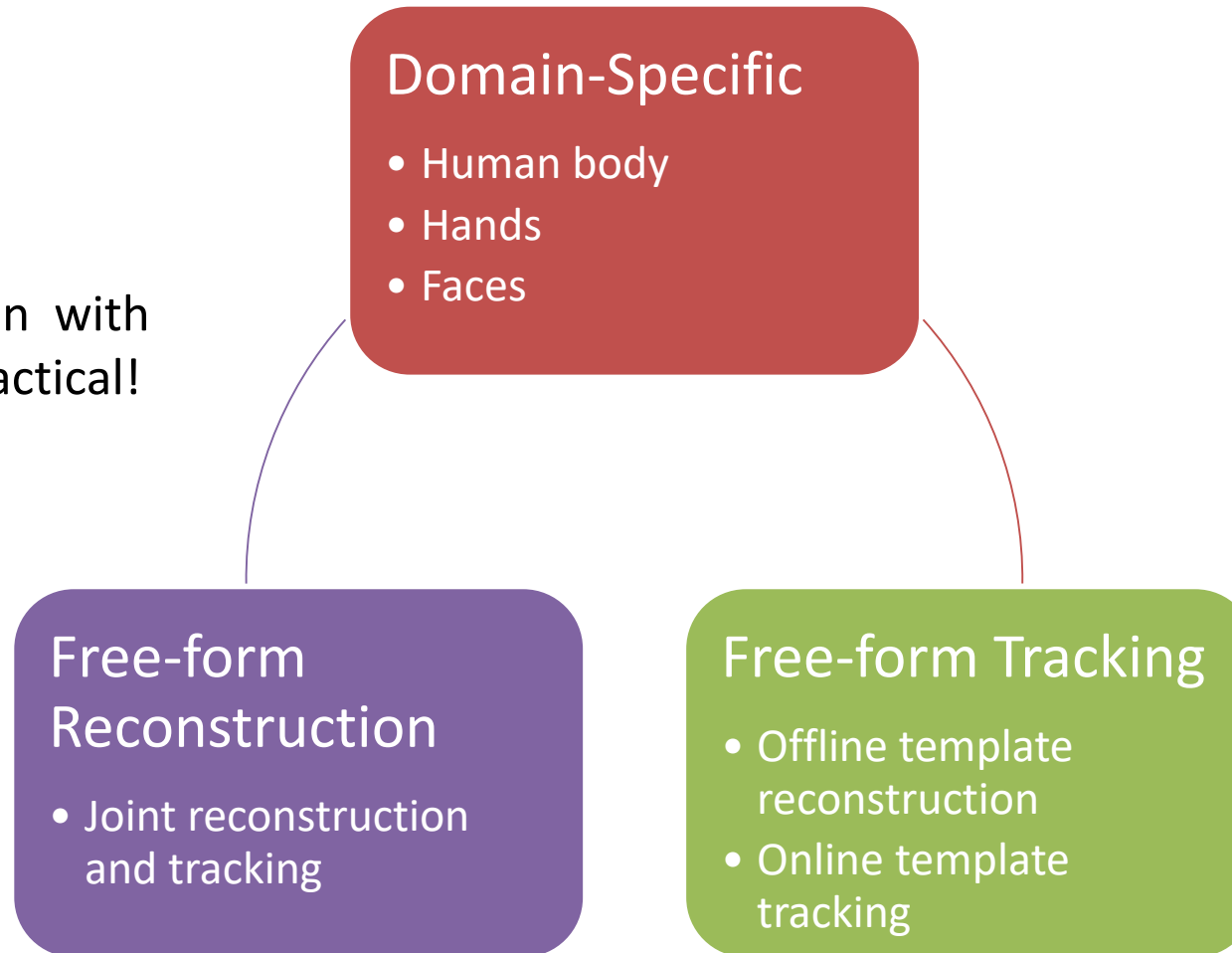
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# Today: Parametric Face Models

# Dynamic 3D Capture

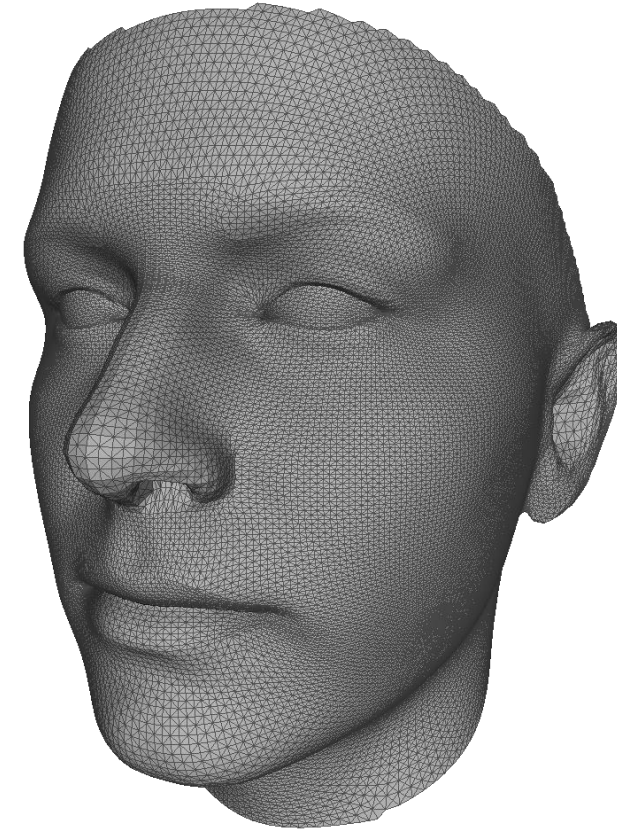
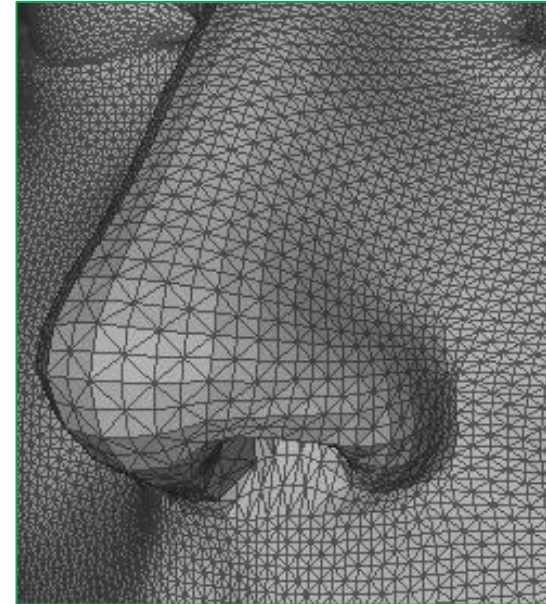
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Need more regularization with fewer DoF to make it practical!



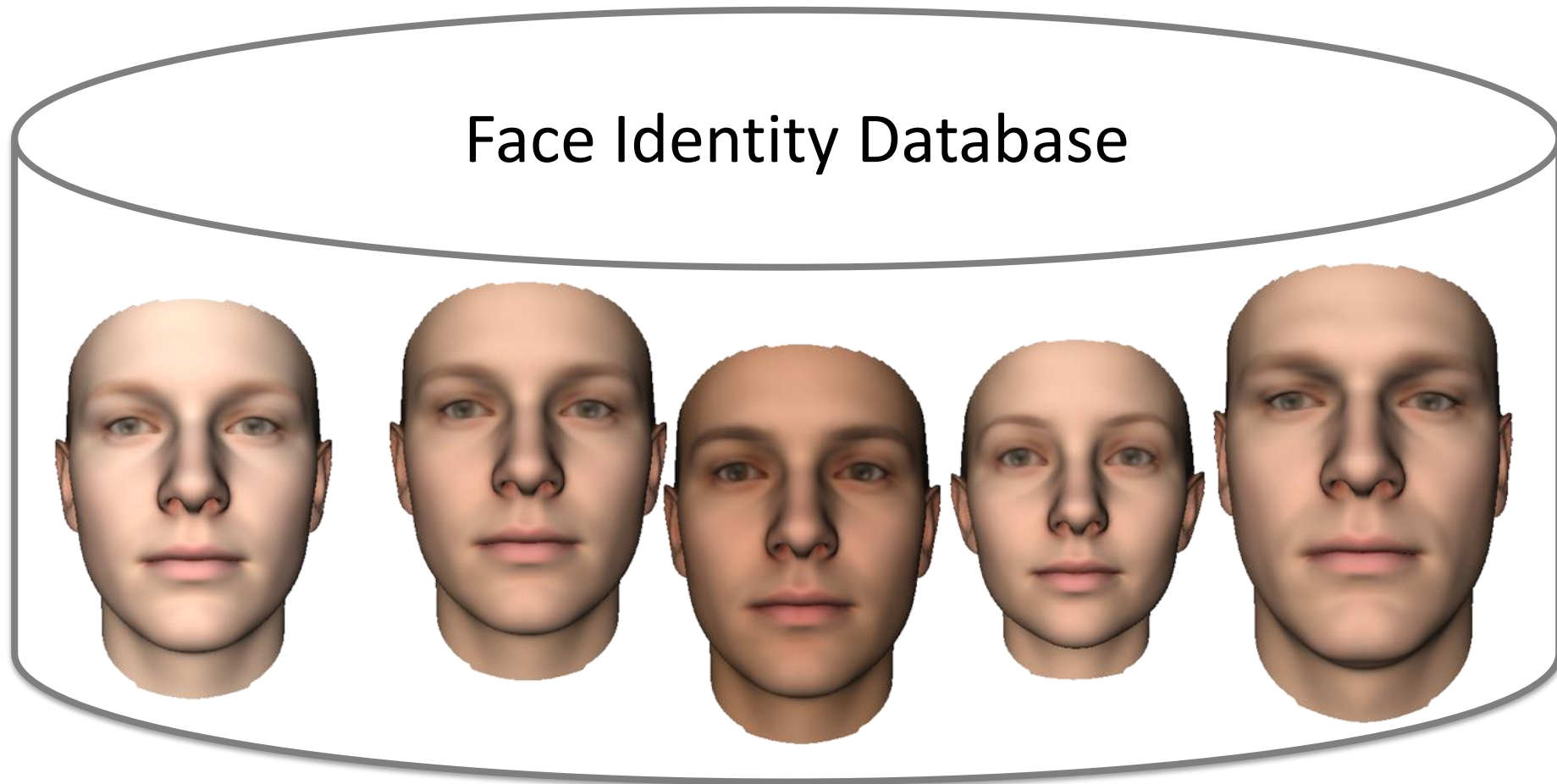
# Parametric Models -> Dimensionality Reduction

- Small number of parameters change larger number of vertices
  - E.g., basis functions + skinning
- For Faces, Hands, Bodies
- Simplest one:
  - Rigid 6-DOF poses between frames
    - 6 parameters transform entire frames
    - Nobody would really call it this way



# Parametric Face Model: Shape Identity

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# Parametric Face Model: Shape Identity

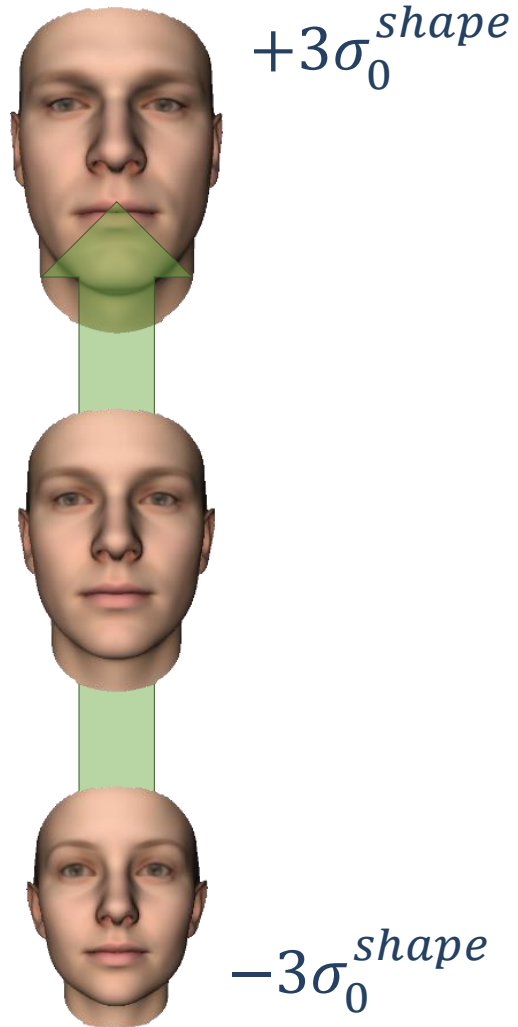
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Average Face

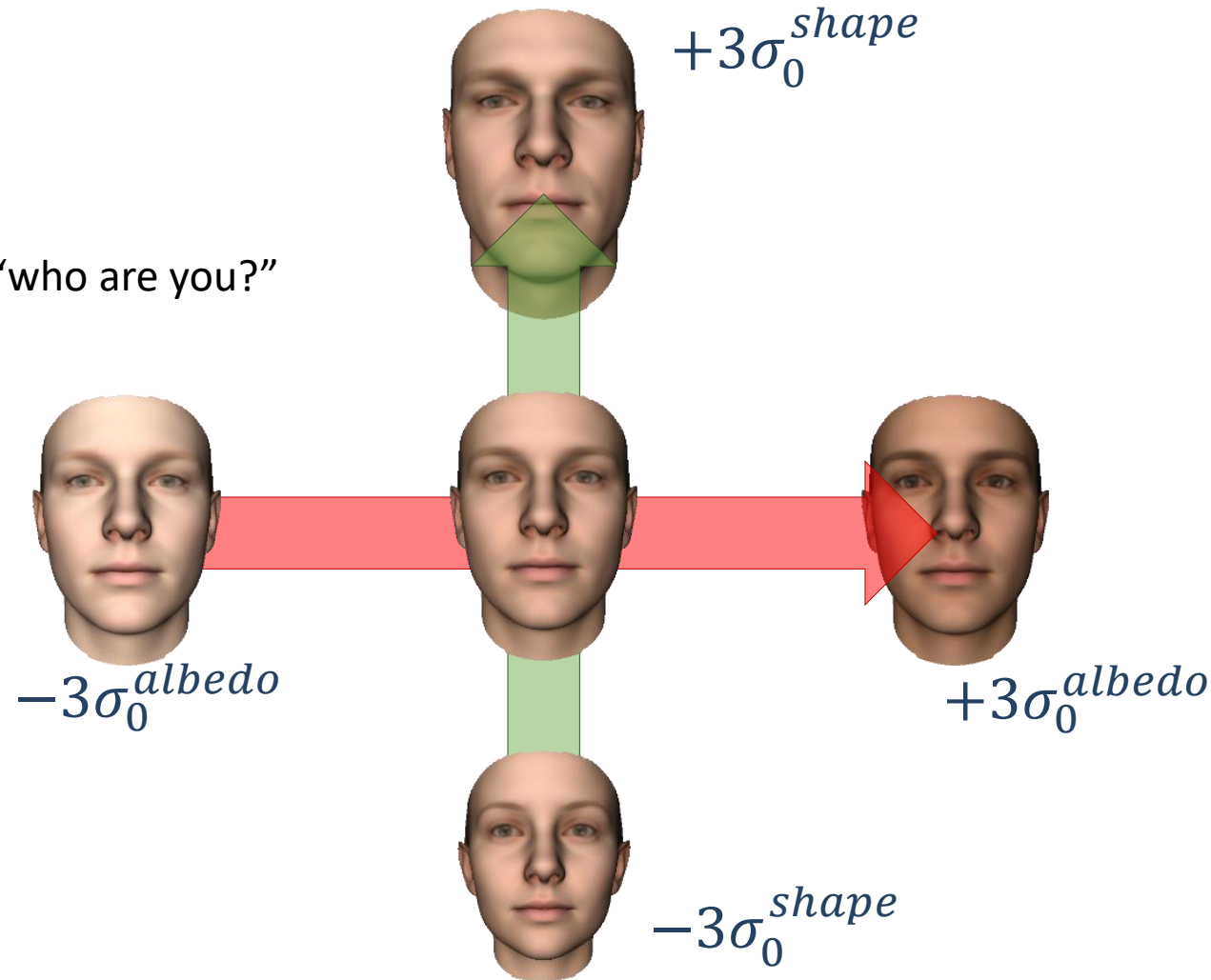
# Parametric Face Model: Shape Identity

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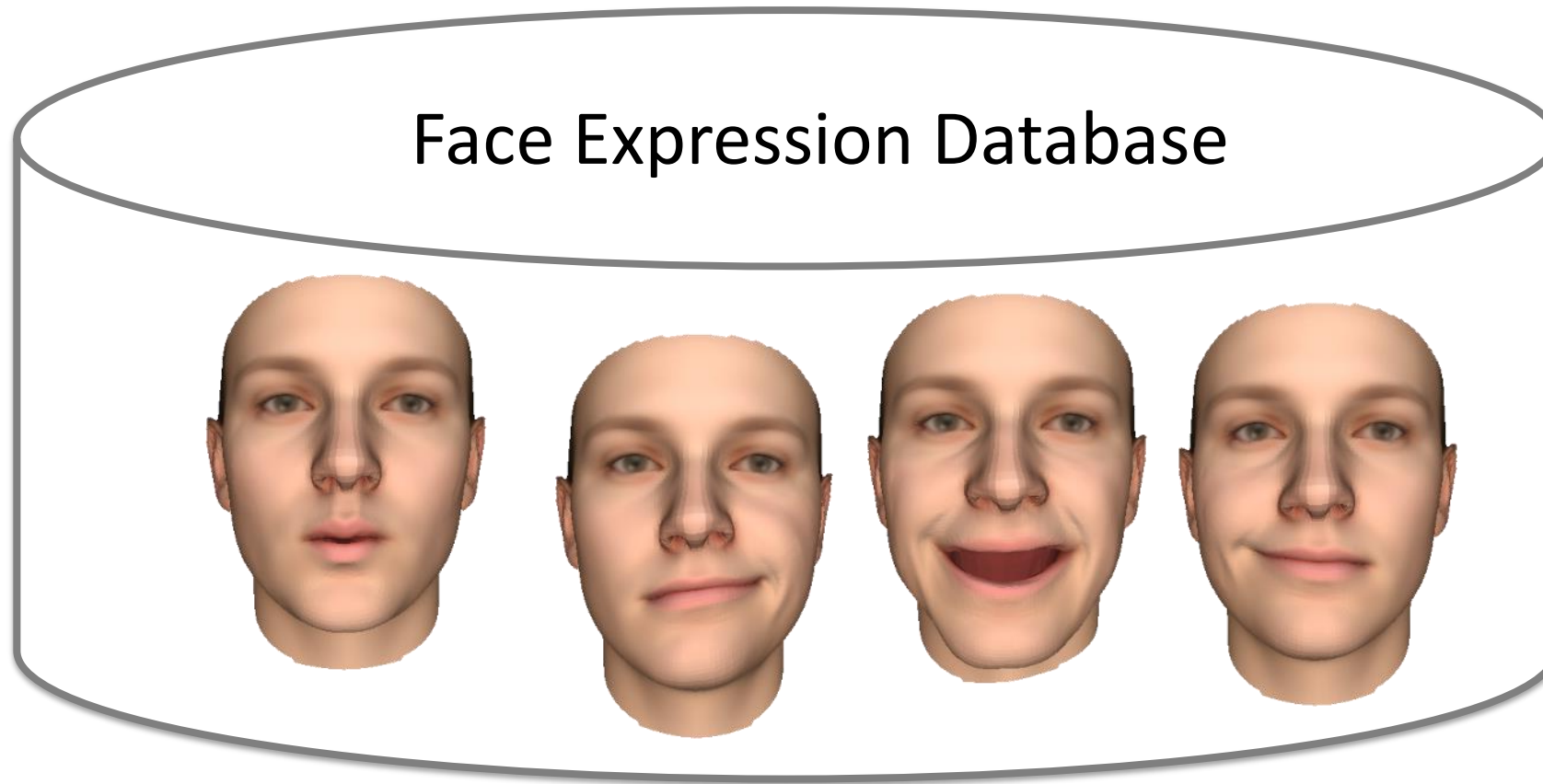
# Parametric Face Model: Shape Identity

Shape Identity defines “who are you?”



# Parametric Face Model

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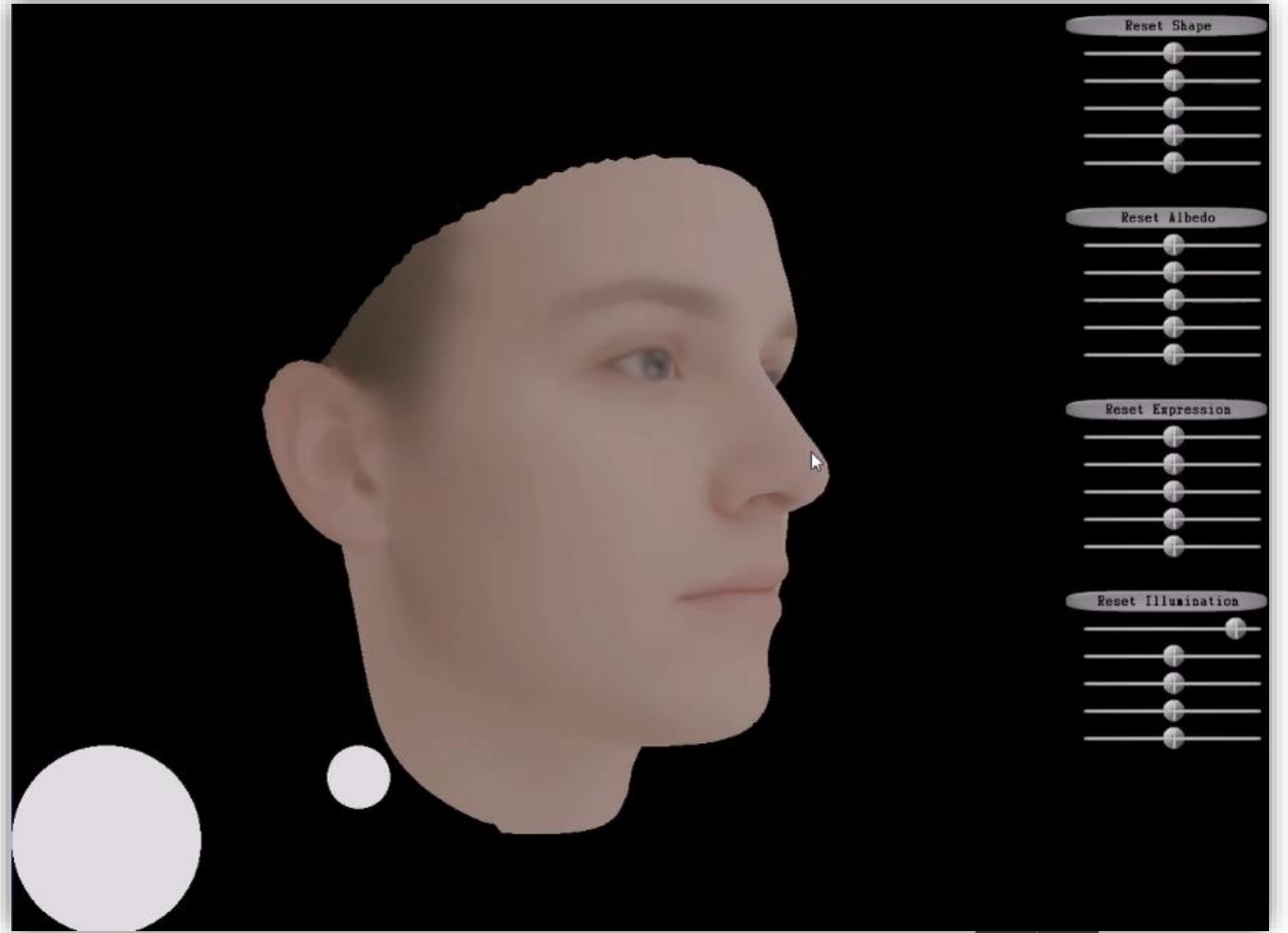


# Parametric Face Model

Rigid Pose

$$\mathbf{P} = \begin{pmatrix} \Phi \end{pmatrix}$$

$$|\mathbf{P}| = 6$$

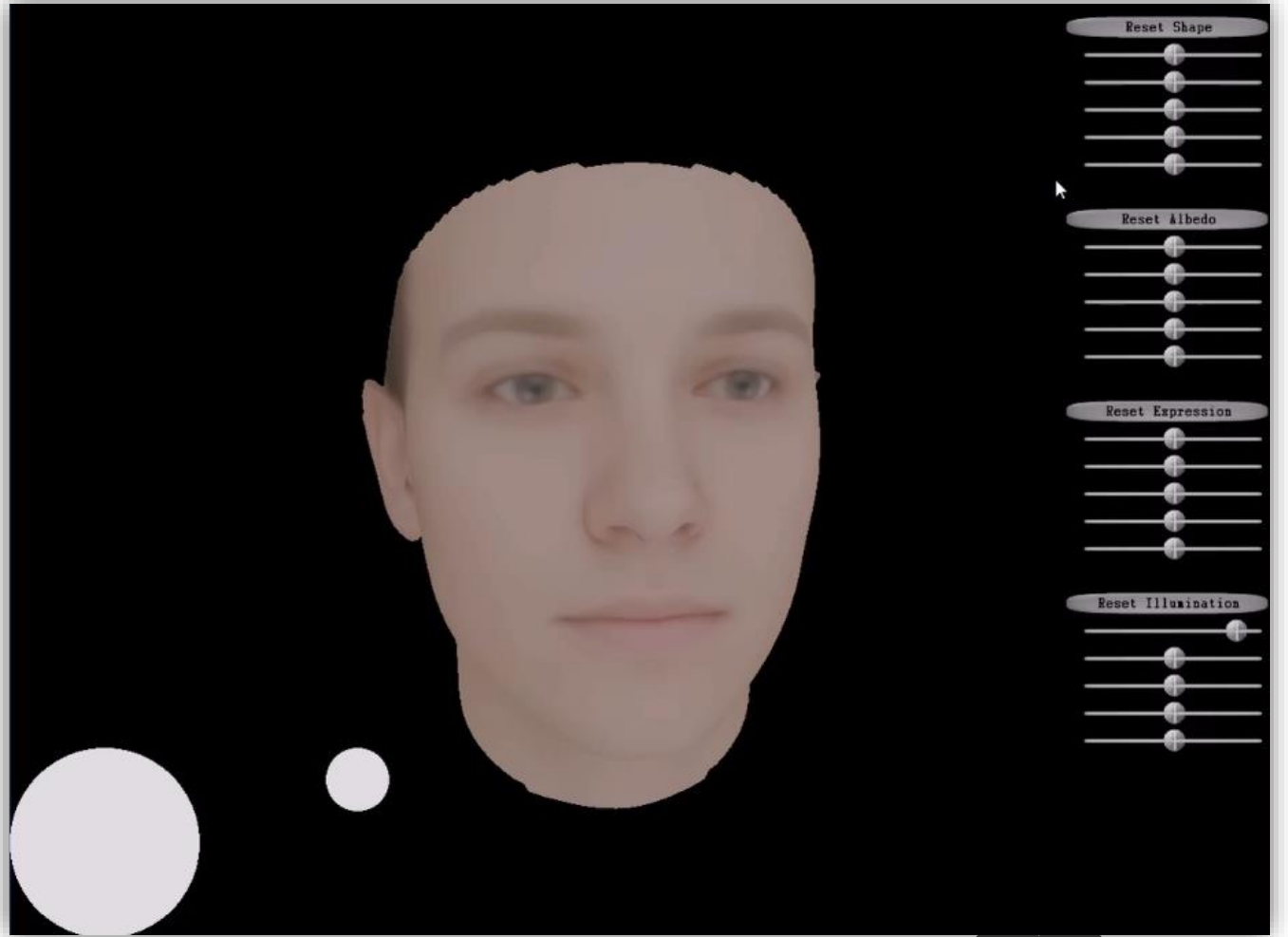


# Parametric Face Model

Shape Identity

$$\mathbf{P} = \begin{pmatrix} \Phi \\ \alpha \end{pmatrix}$$

$$|\mathbf{P}| = 6 + 80$$

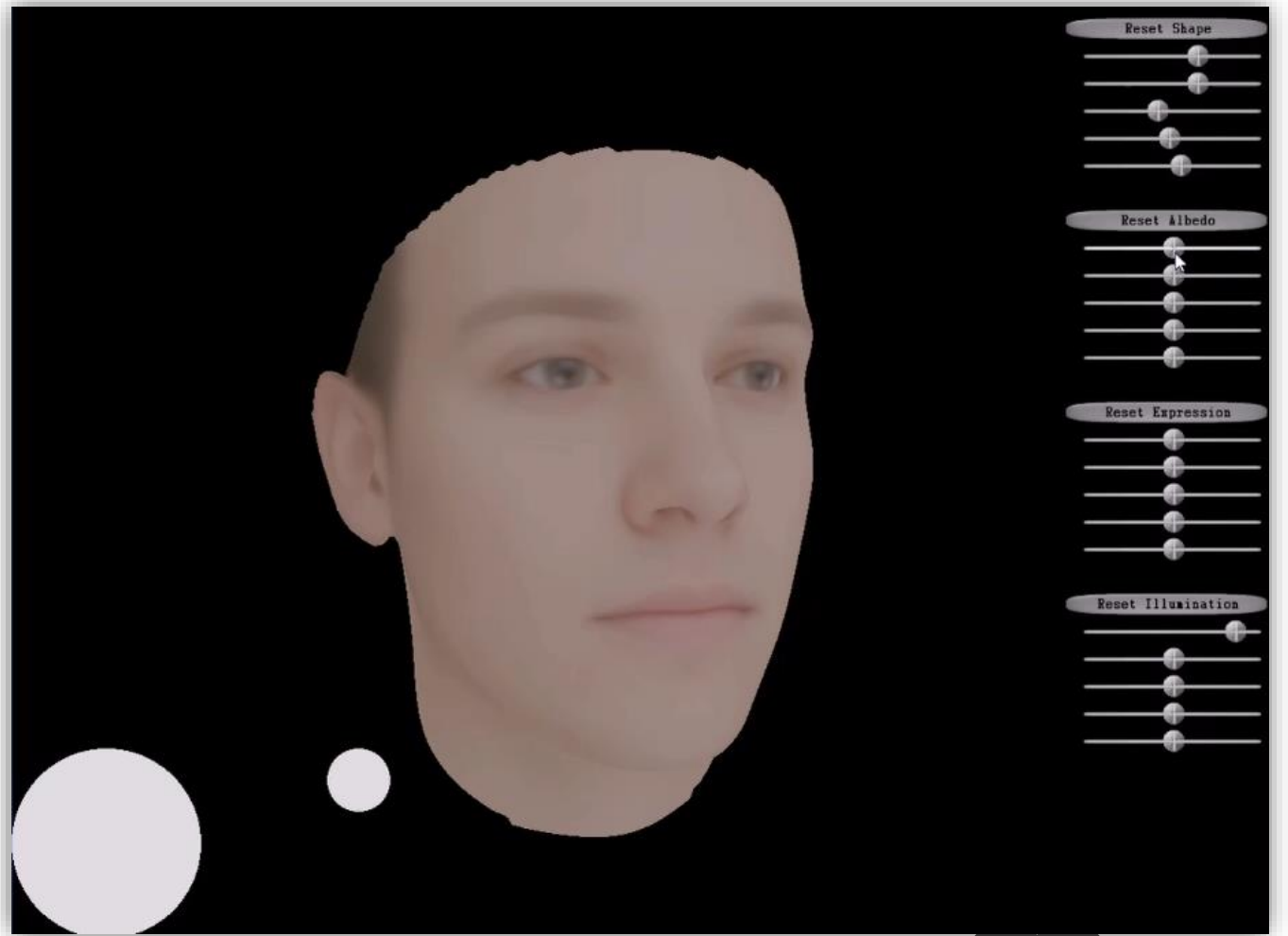


# Parametric Face Model

Material / Reflection

$$\mathbf{P} = \begin{pmatrix} \Phi \\ \alpha \\ \beta \end{pmatrix}$$

$$|\mathbf{P}| = 6 + 80 + 80$$

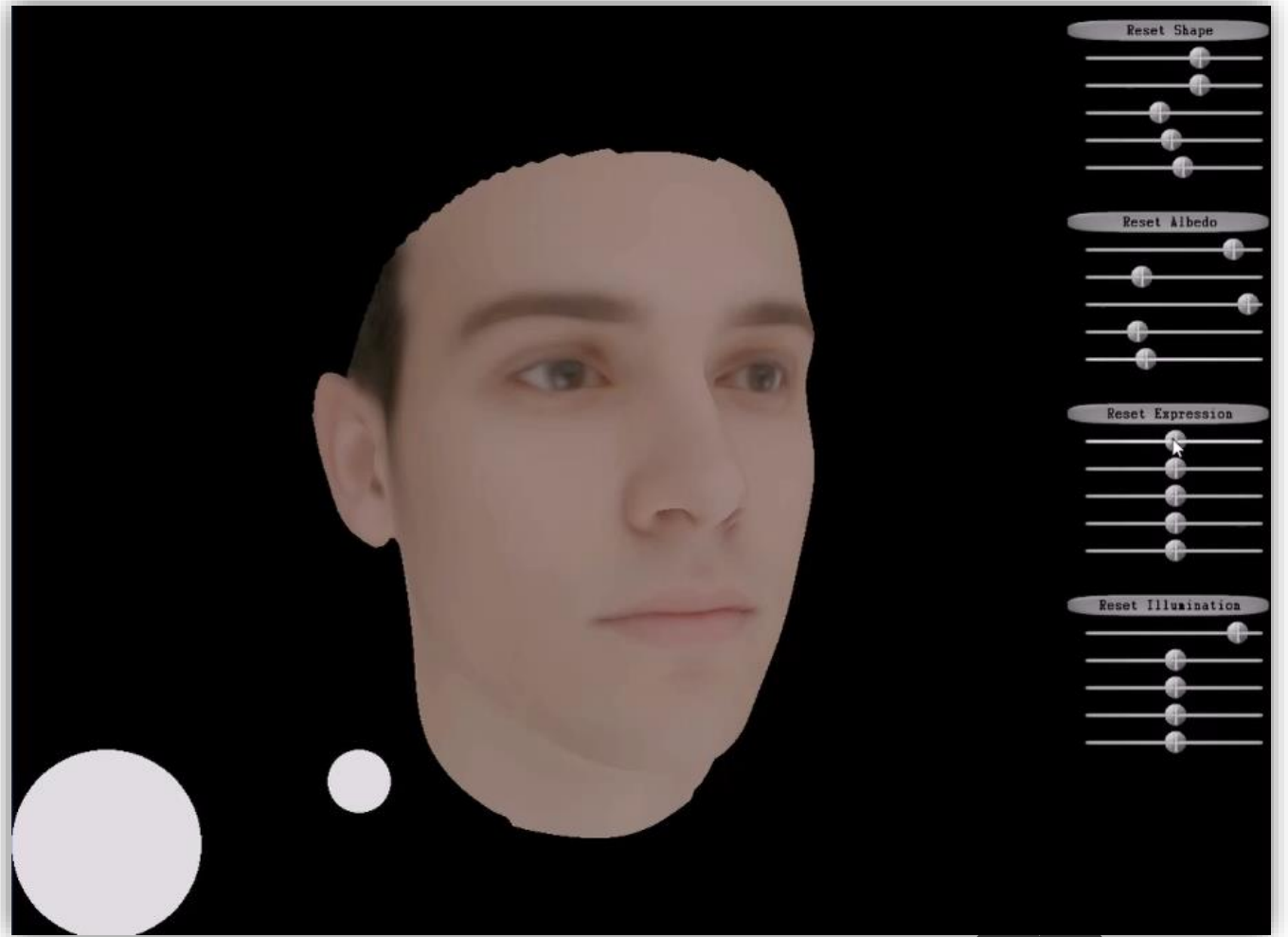


# Parametric Face Model

Expression Parameters

$$\mathbf{P} = \begin{pmatrix} \Phi \\ \alpha \\ \beta \\ \delta \end{pmatrix}$$

$$|\mathbf{P}| = 6 + 80 + 80 + 76$$



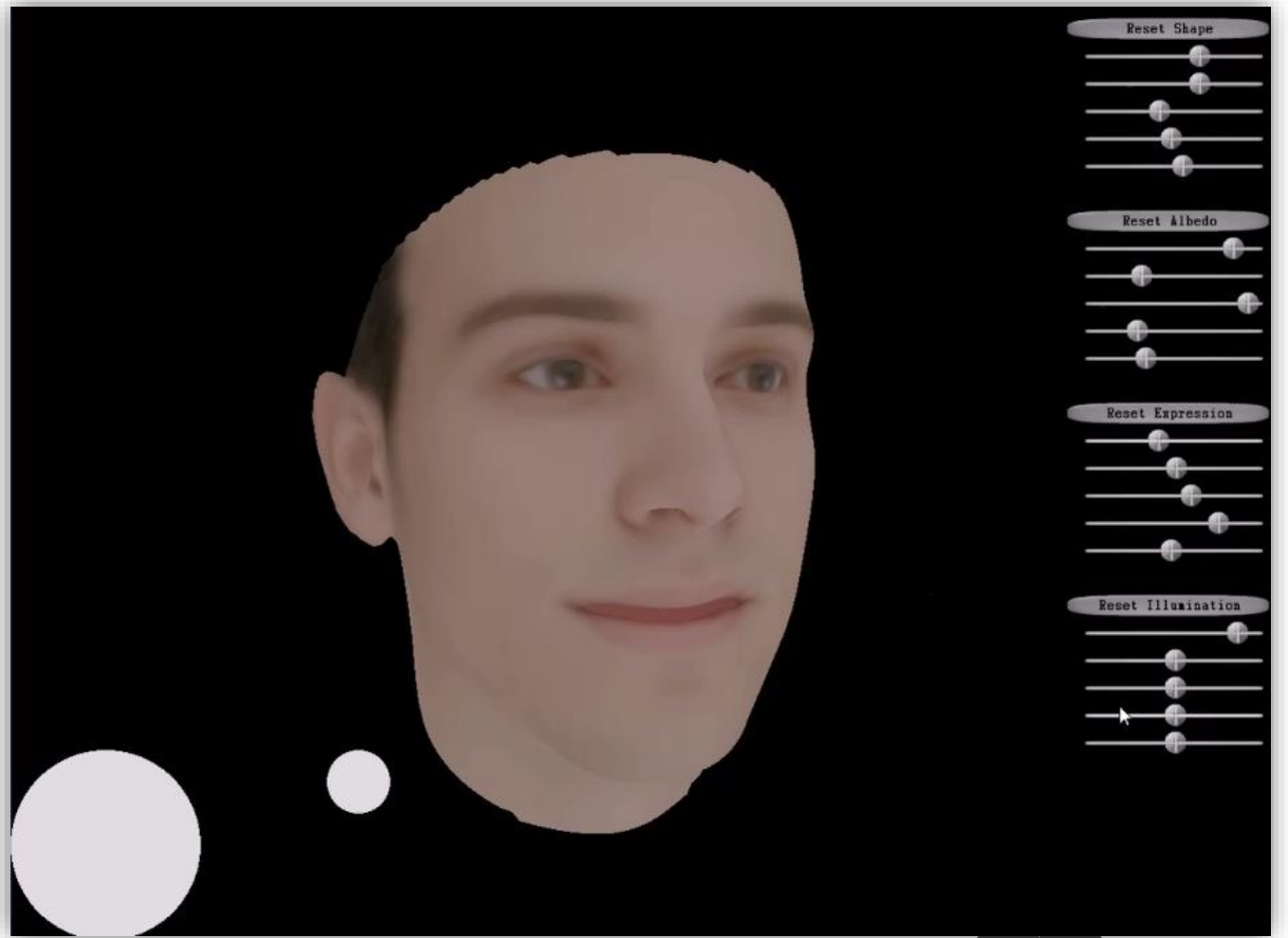


# Parametric Face Model

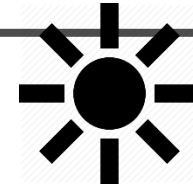
Lighting Parameters

$$\mathbf{P} = \begin{pmatrix} \Phi \\ \alpha \\ \beta \\ \delta \\ \gamma \end{pmatrix}$$

$$|\mathbf{P}| = 6 + 80 + 80 + 76 + 27$$



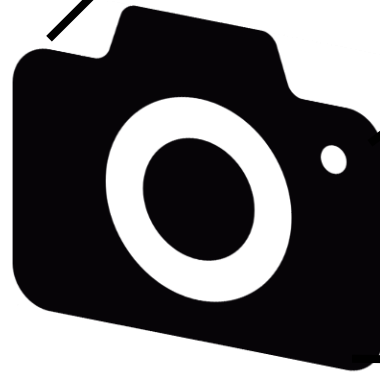
# Illumination Models



Light Source



2D Image

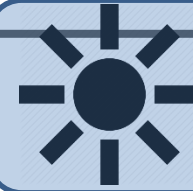


Camera



3D Face

# Illumination Models



Light Source



2D Image



Camera



3D Face

# Illumination Models

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- Lighting-face interaction is complex (e.g., highlights, scattering)
  - Advanced light transport models intractable for face reconstruction
- Simplified yet reasonable representations:
  - Environment map
  - Spherical harmonics

# Illumination Models

- Environment maps [Klehm et al. '15]



Scene lighting



Cube map

Sphere map



- Assumptions:

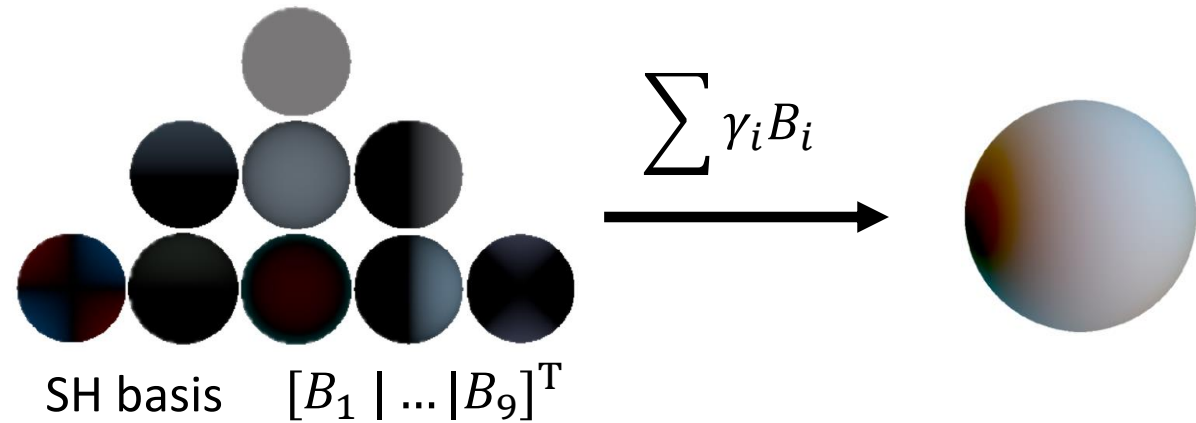
- Distant lighting
- No self shadows, no scattering

# Illumination Models

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## ➤ Spherical Harmonics [Mueller '66]

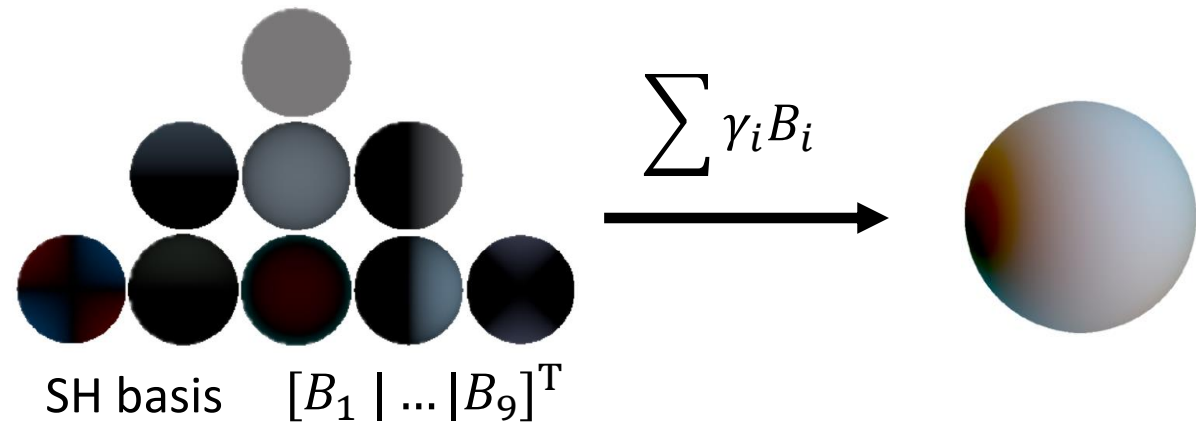
- Orthogonal basis
- Defined over a sphere



# Illumination Models

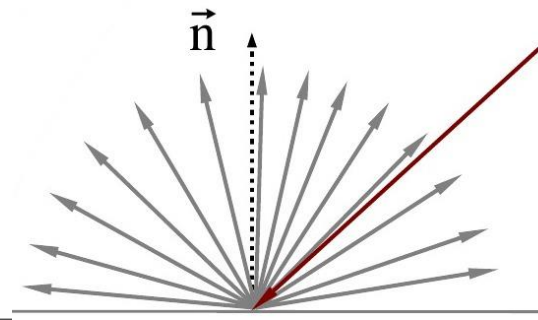
## ➤ Spherical Harmonics [Mueller '66]

- Orthogonal basis
- Defined over a sphere



## ➤ Assumptions:

- Lambertian surface
- Distant smooth lighting



$$L = \sum \gamma_i B_i(\vec{n})$$

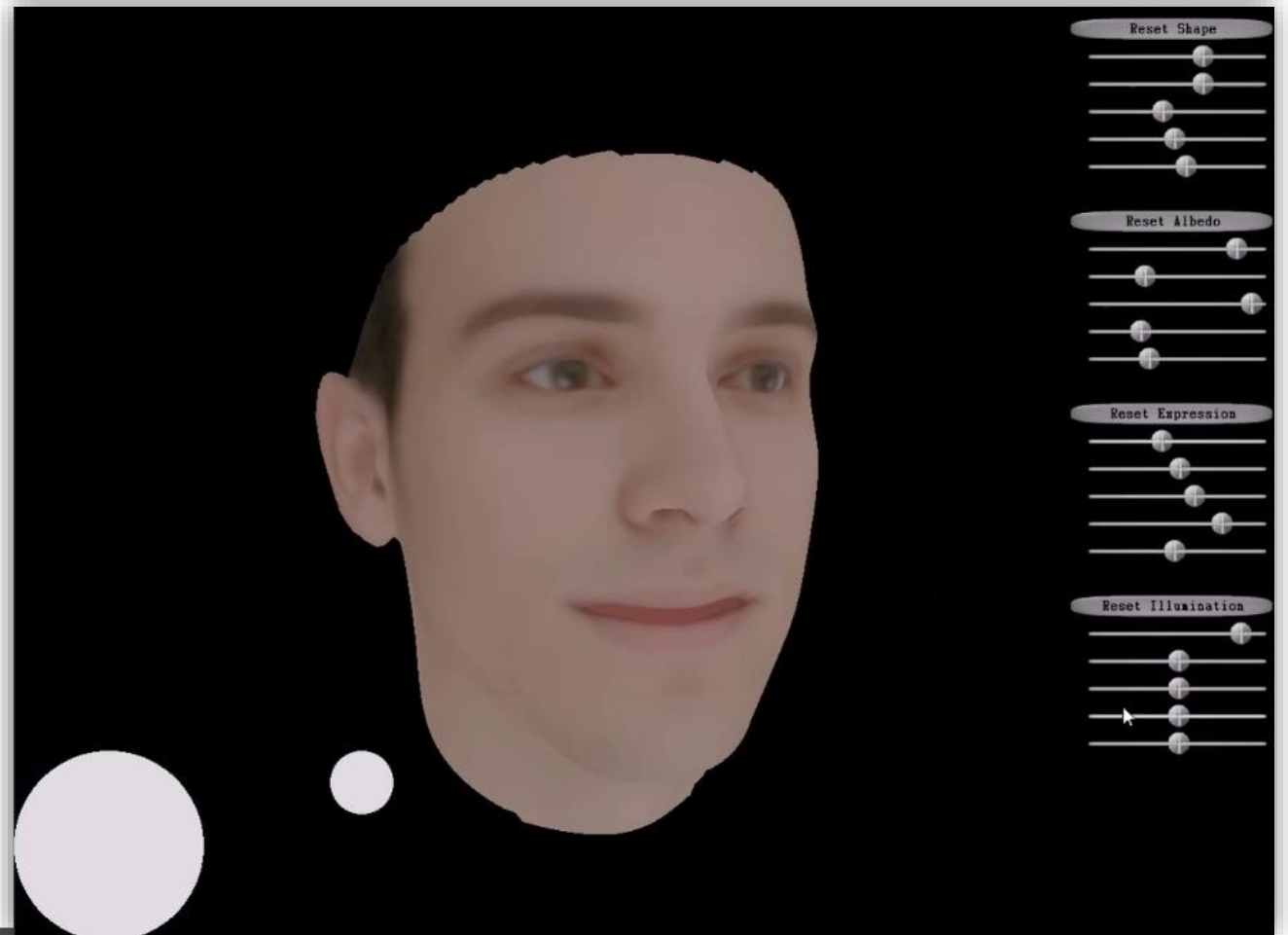
# Illumination Models

## ➤ Spherical Harmonics [Mueller '66]

- Orthogonal basis
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## ➤ Assumptions:

- Lambertian surface
- Distant smooth lighting





# Parametric Model

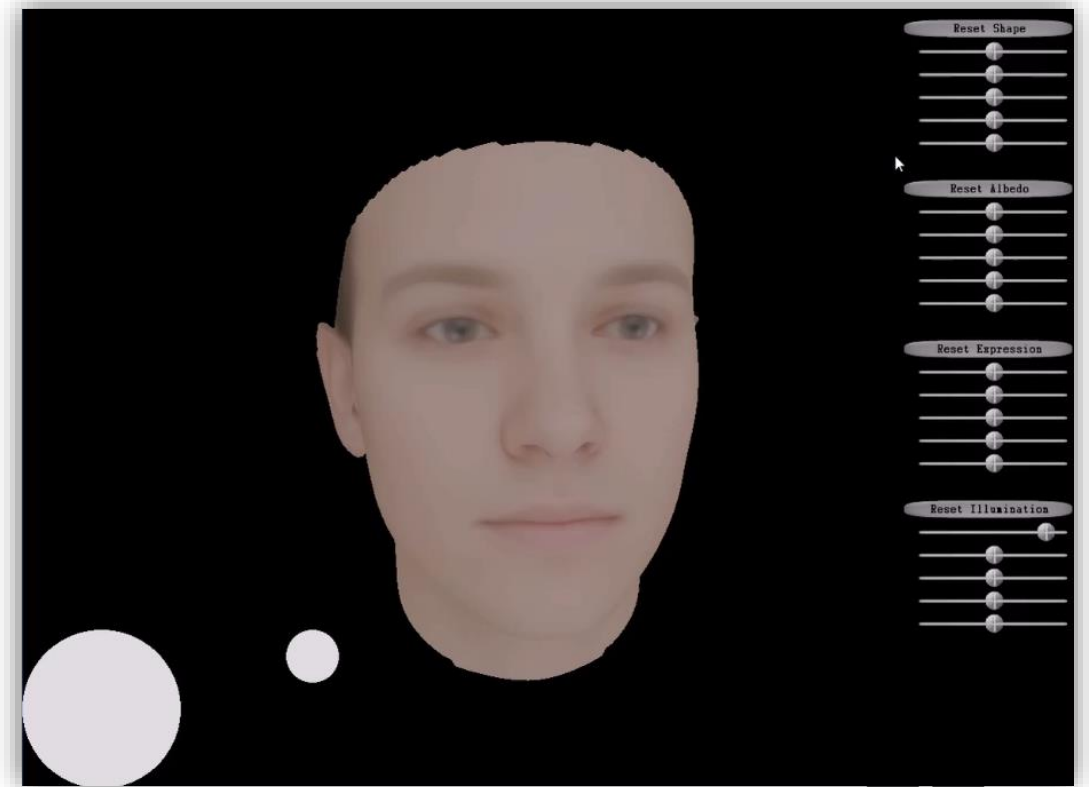
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- Morphable model [Blaiz & Vetter '99]
  - Derived from 200 neutral scans (100 male + 100 female)
  - Two independent PCA models:

# Parametric Model

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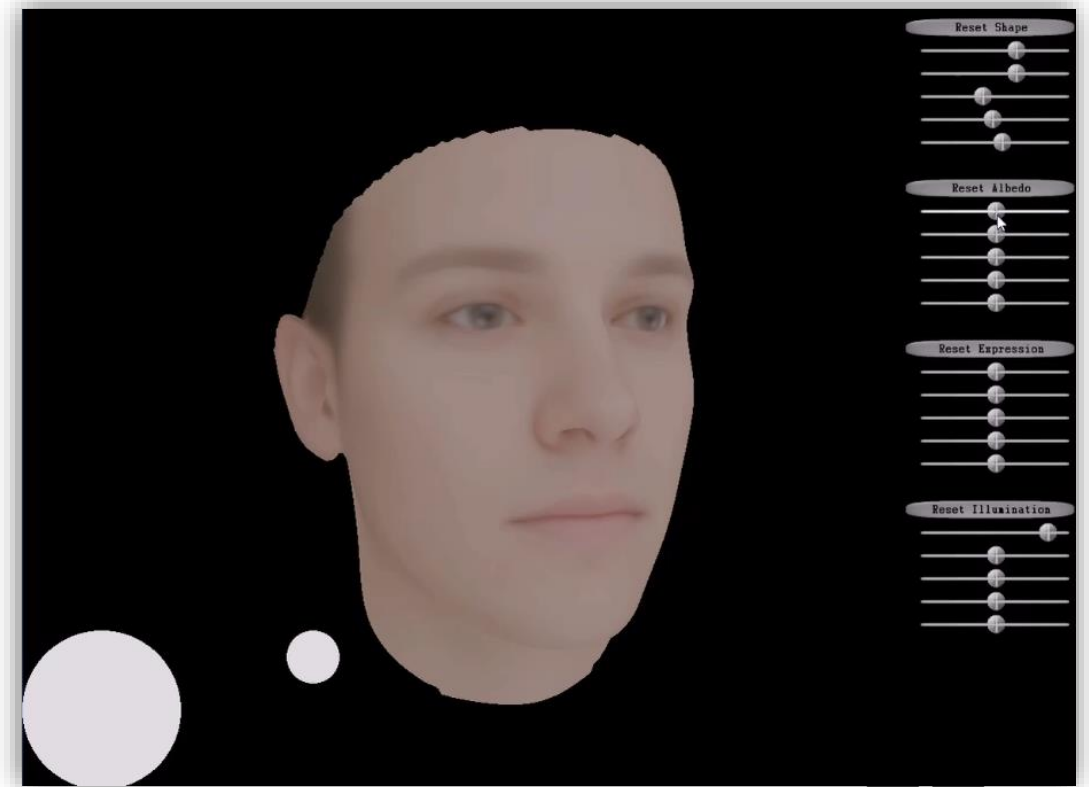
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    - Identity



# Parametric Model

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- Morphable model [Blanz & Vetter '99]
  - Derived from 200 neutral scans (100 male + 100 female)
  - Two independent PCA models:
    - Identity
    - Albedo



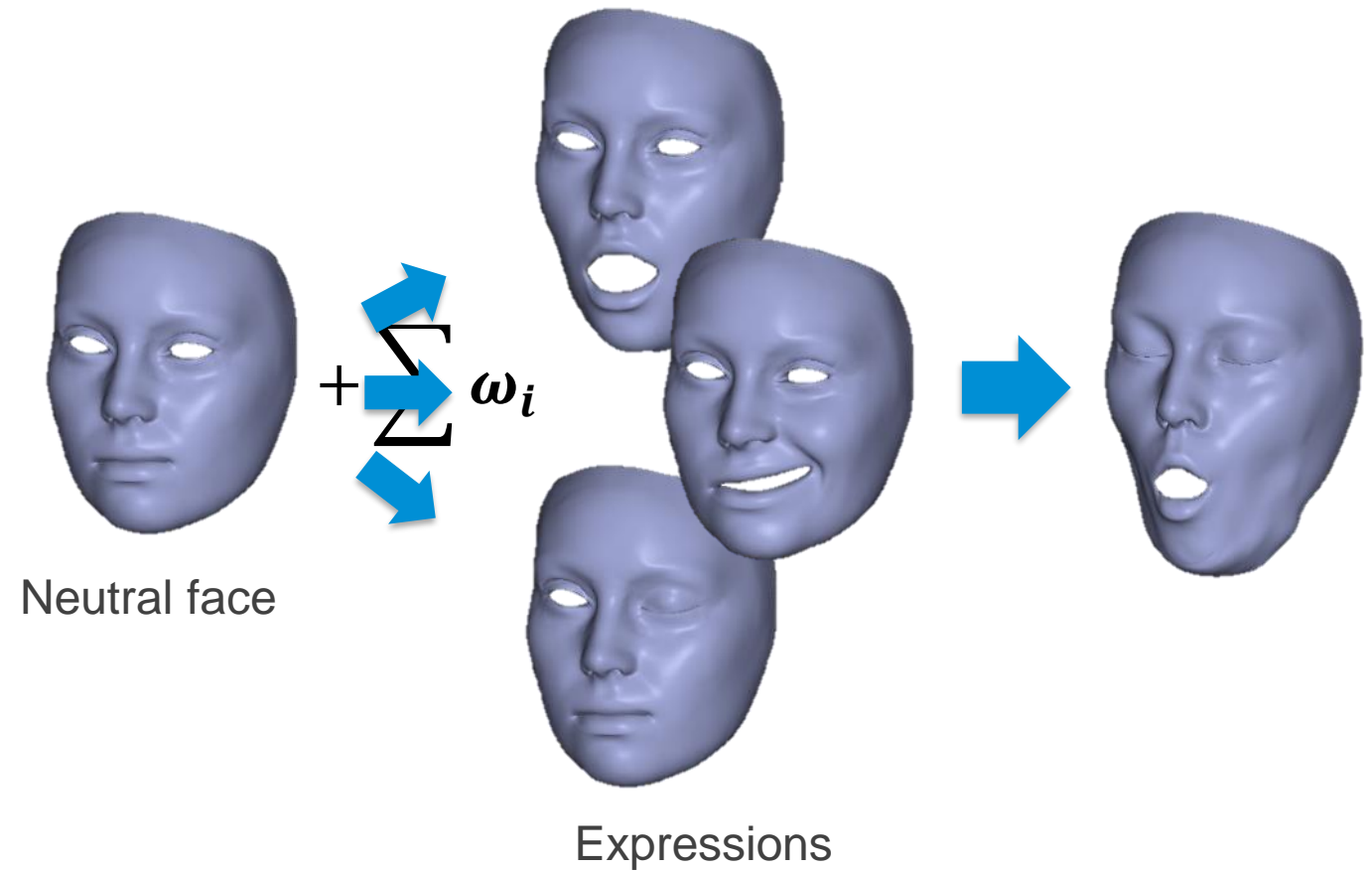
# Parametric Model

---

- Morphable model [Blanz & Vetter '99]
  - Derived from 200 neutral scans (100 male + 100 female)
  - Two independent PCA models:
    - Identity
    - Albedo
- Drawbacks
  - Population bias (mainly Caucasians)
  - Parameters have global influence
  - No semantic deformations

# Parametric Model

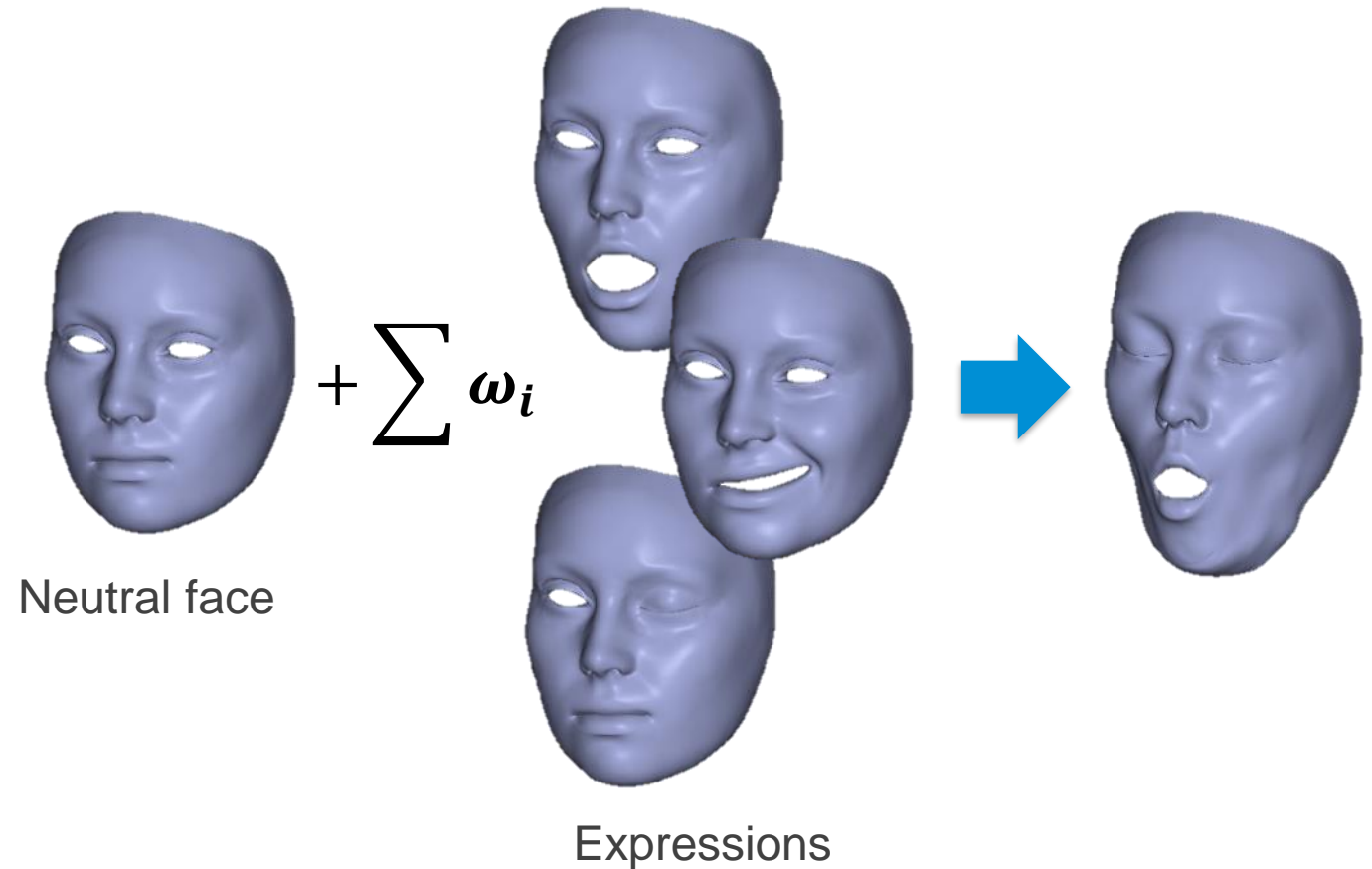
- Blendshapes [Lewis et al. '14]
  - Additive model
  - Controlled via blendshape weights



# Parametric Model

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- Blendshapes [Lewis et al. '14]
  - Additive model
  - Controlled via blendshape weights
  - Can be customized
- Popular choice
  - Delta blendshapes



# Parametric Model

More personalized;  
Semantically meaningful

More general;  
Less intuitive

# Parametric Model

More personalized;  
Semantically meaningful

More general;  
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**Morphable model**  
[Blanz&Vetter '99; ...]

**Multilinear model**  
[Vlasic et al. '05;  
Cao et al. '14;  
Shi et al. '14]

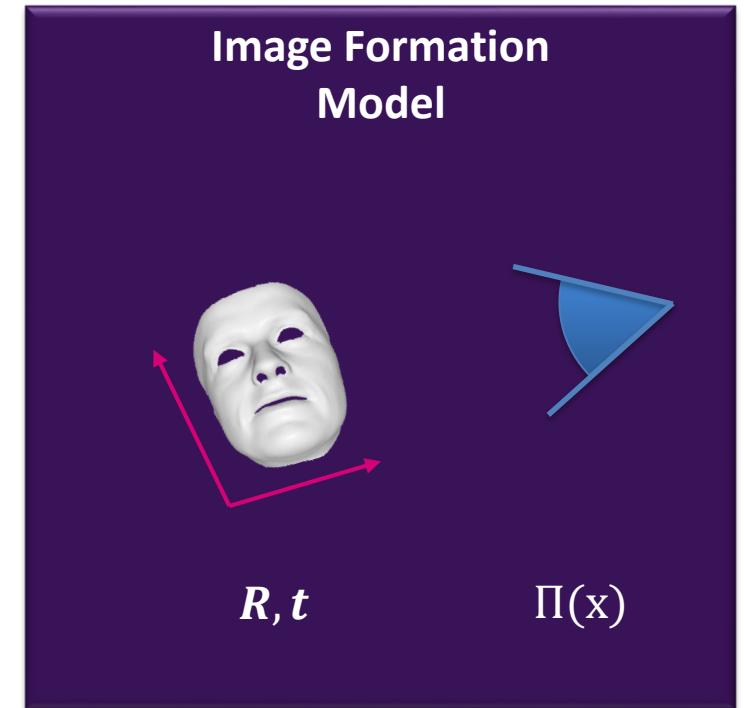
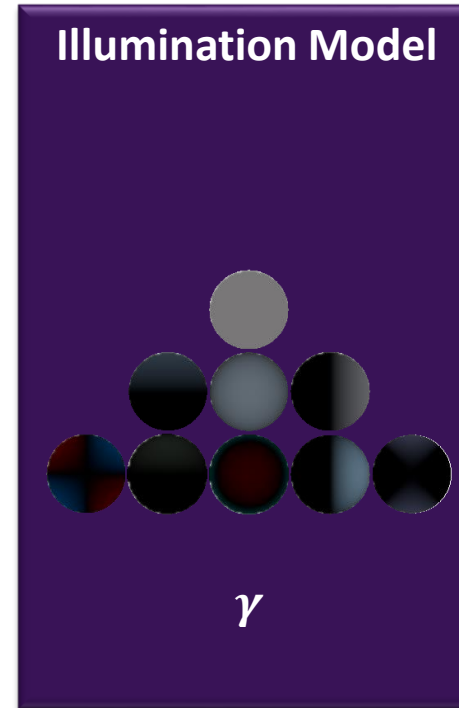
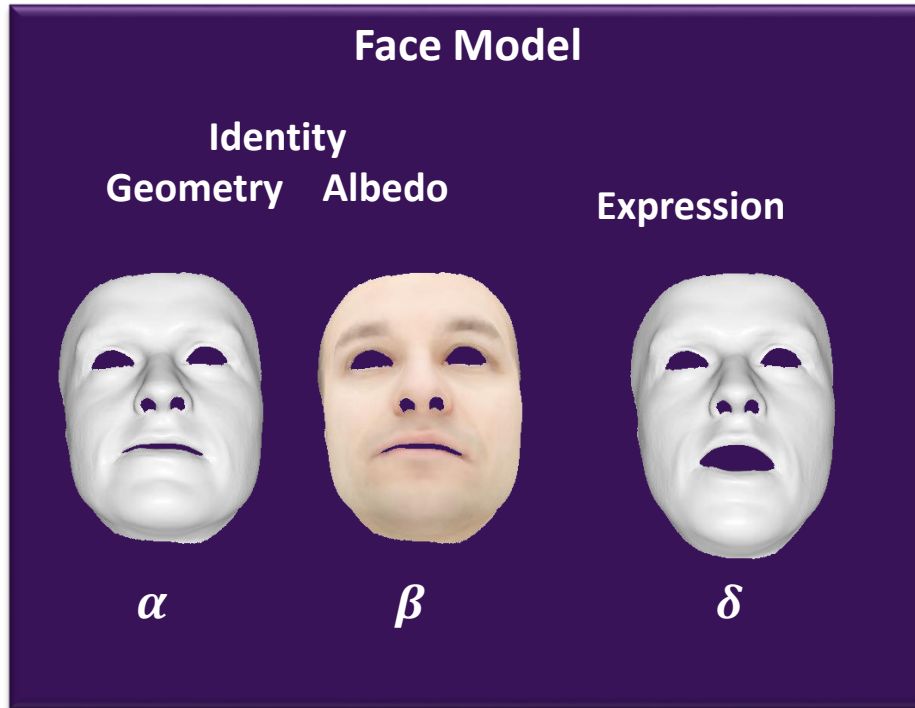
**Blendshapes**  
[Garrido et al. '13;  
Wu et al. '16;  
Thies et al. '16]

**Adaptive blendshapes**  
[Bouaziz et al. '13;  
Li et al. '13;  
Hsieh et al. '15]

**Face rigs**  
[Ichim et al. '15;  
Garrido et al. 16]



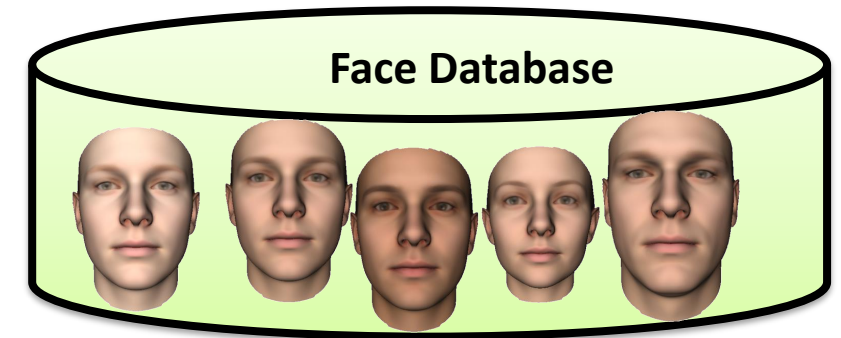
# Parametric Face Model



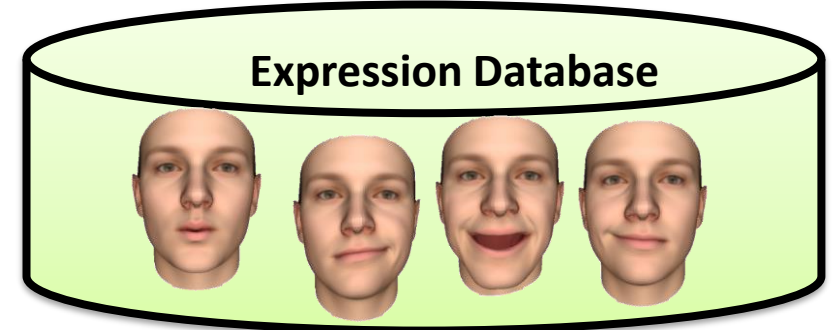
# Parametric Face Model

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- Offline / “Learning Phase”: Model Construction



- Run time / “Test Phase”: Model Fitting



# How to Construct a Parametric Face Model?

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- Assume we have a set of meshes of the face with the same topology but different poses
- Then, we have 1:1 correspondences between the vertices
- Basis functions are given through PCA of mesh (linear model)

# How to Construct a Parametric Face Model?

---

- Compute face prior:
  - Scan a few hundred faces/expressions and fit a topologically-consistent template to each scan using non-rigid registration
  - Compute PCA-basis for identity and expressions
- At runtime: fit prior to input data

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  - Compute PCA-basis for identity and expressions
- At runtime: fit prior to input data
  - E.g., from a sparse set of keypoints
  - E.g., from depth data
  - E.g., from RGB data

# How to Construct a Parametric Face Model?

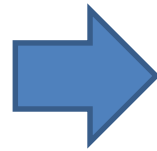
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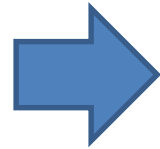


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KinectFusion

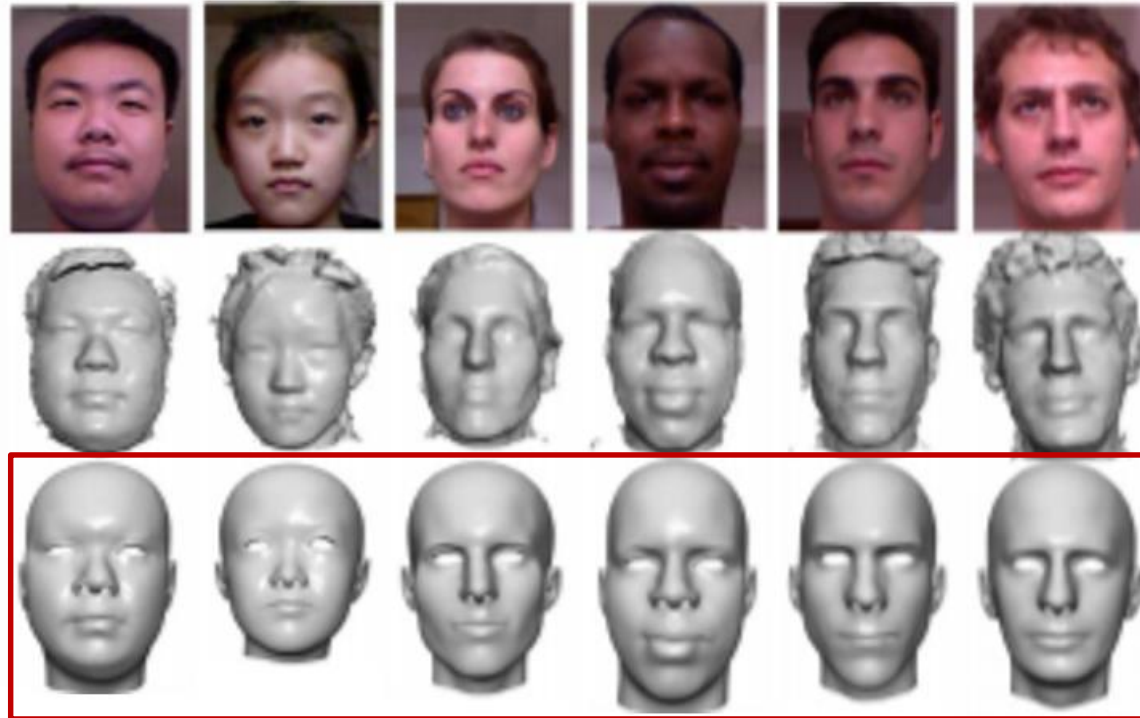


Cao et al. “FaceWarehouse”



# How to Construct a Parametric Face Model?

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Cao et al. “FaceWarehouse”

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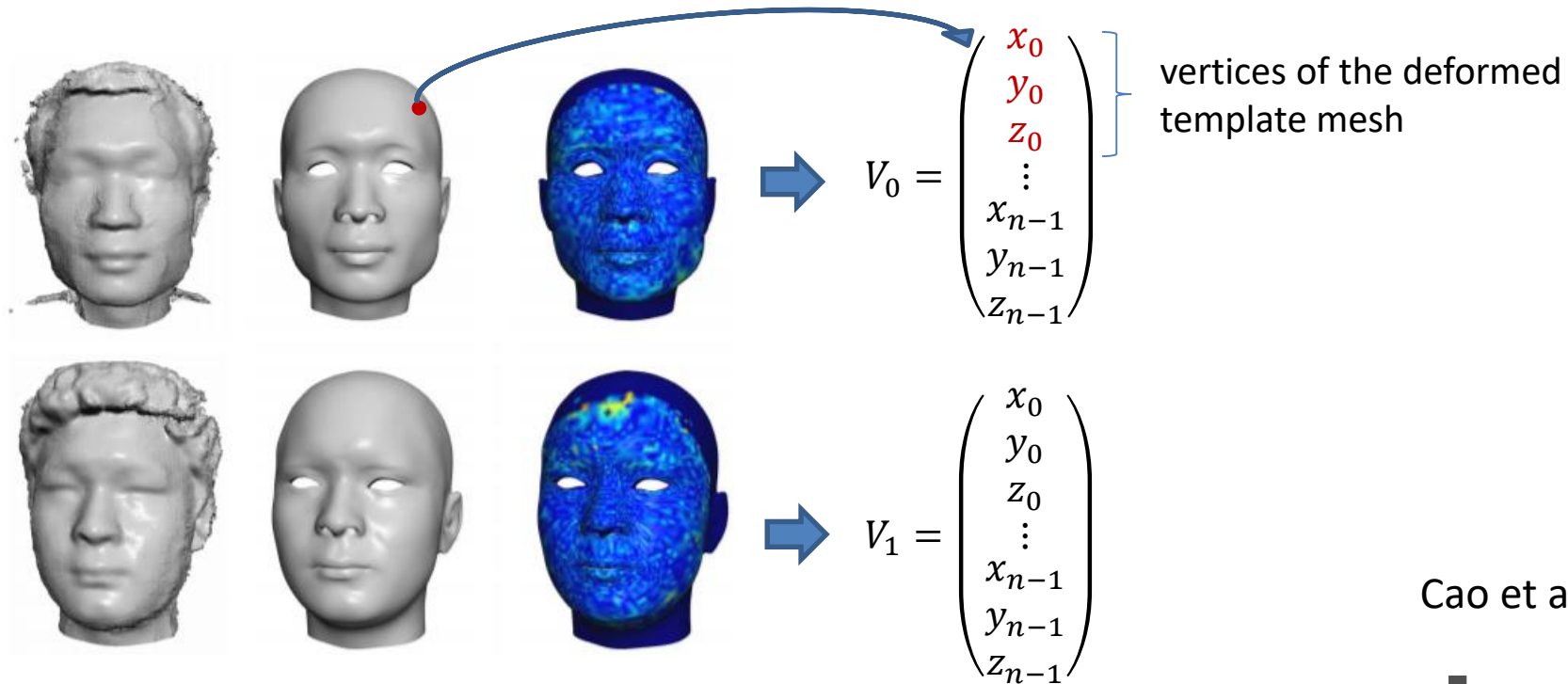
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  - **Compute PCA-basis** for identity [and expressions]

$$V_0 = \begin{pmatrix} x_0 \\ y_0 \\ z_0 \\ \vdots \\ x_{n-1} \\ y_{n-1} \\ z_{n-1} \end{pmatrix} \cdots V_{m-1} = \begin{pmatrix} x_0 \\ y_0 \\ z_0 \\ \vdots \\ x_{n-1} \\ y_{n-1} \\ z_{n-1} \end{pmatrix} \xrightarrow{\text{PCA}}$$

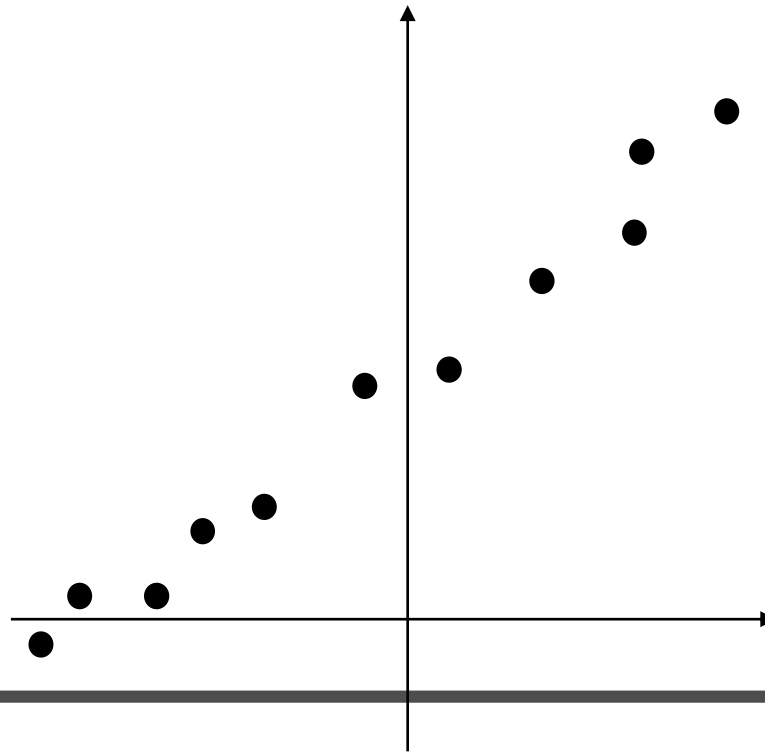
Average:  $\bar{V}$   
Principle Components:  $\vec{E}_0 \cdots \vec{E}_{m-2}$   
Std. Deviation:  $\sigma_0 \cdots \sigma_{m-2}$

# Principle Component Analysis (PCA)

---

- Compute mean:

$$\bar{\mathbf{X}} = \frac{1}{N} \sum_i \mathbf{X}_i, \quad \bar{\mathbf{X}}_i = \mathbf{X}_i - \bar{\mathbf{X}}$$

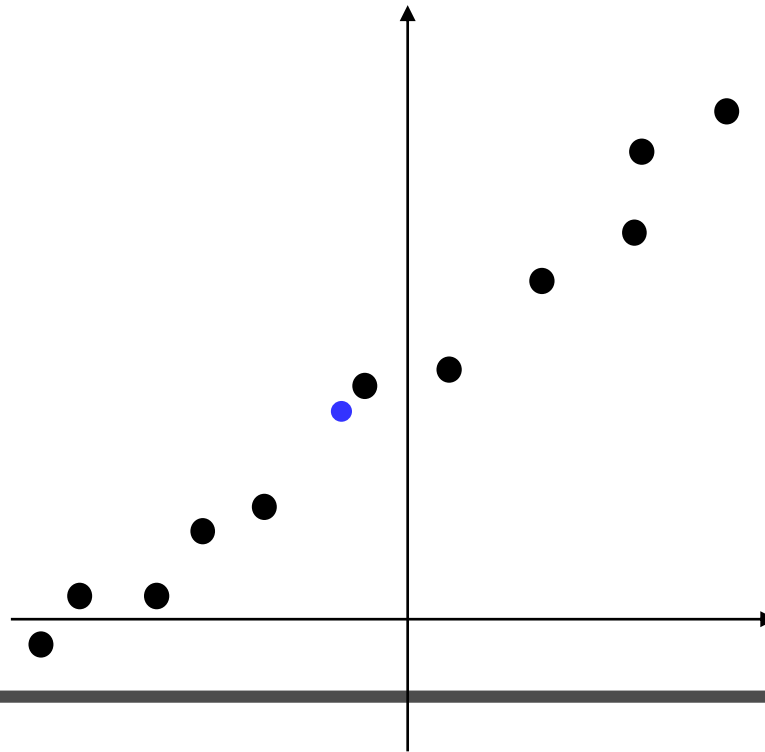


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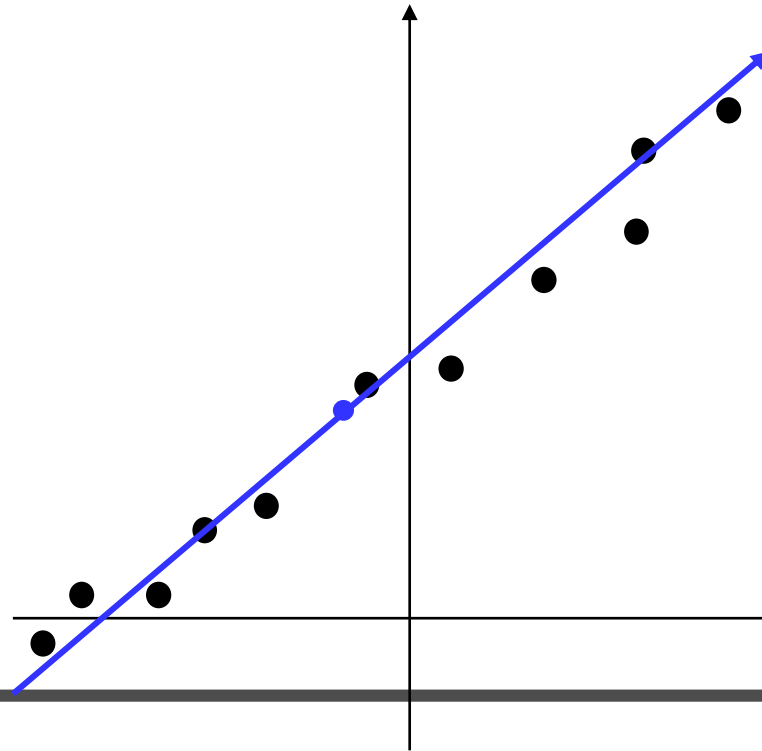
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- Compute principle components of the dataset  $\bar{\mathbf{X}}_i$

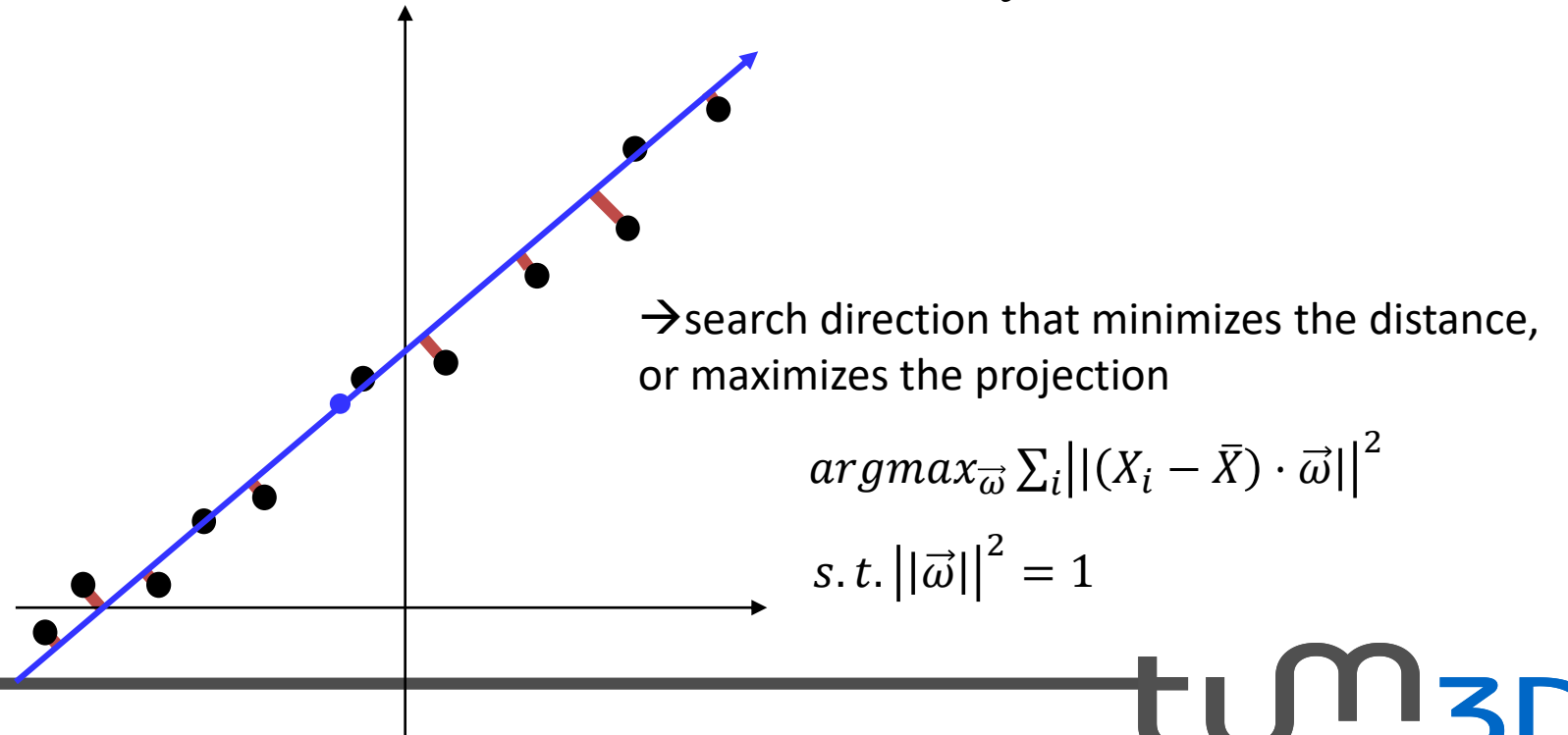


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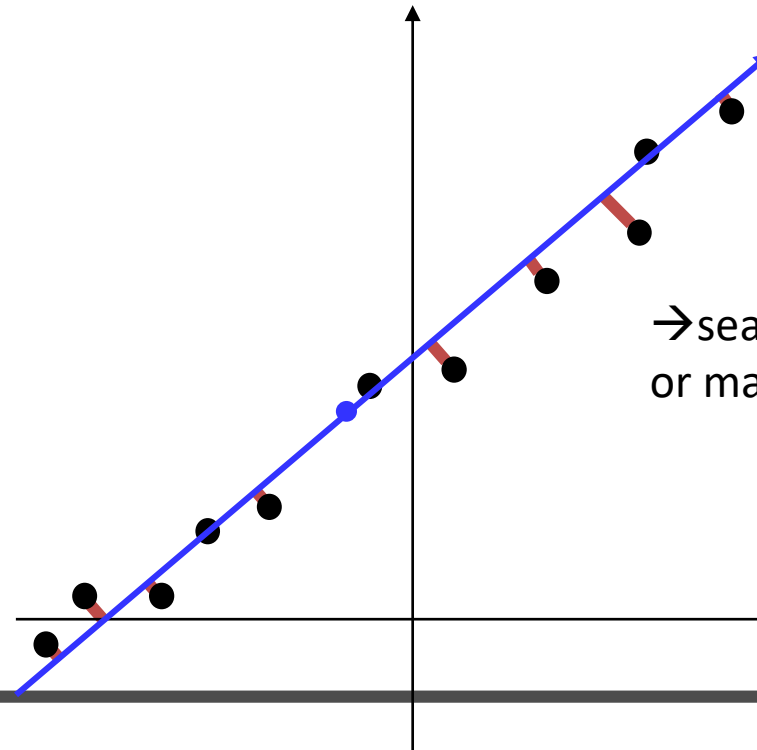


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- Compute principle components of the dataset  $\bar{\mathbf{X}}_i$



→ search direction that minimizes the distance,  
or maximizes the projection

$$\operatorname{argmax}_{\vec{\omega}} \sum_i ||(\mathbf{X}_i - \bar{\mathbf{X}}) \cdot \vec{\omega}||^2$$

$$\text{s. t. } ||\vec{\omega}||^2 = 1$$

**Eigenvectors of the Covariance Matrix**

# Principle Component Analysis (PCA)

---

- Compute mean:

$$\bar{\mathbf{X}} = \frac{1}{N} \sum_i \mathbf{X}_i, \quad \bar{\mathbf{X}}_i = \mathbf{X}_i - \bar{\mathbf{X}}$$

- Compute principle components of the dataset  $\bar{\mathbf{X}}_i$ 
  - Compute covariance matrix:

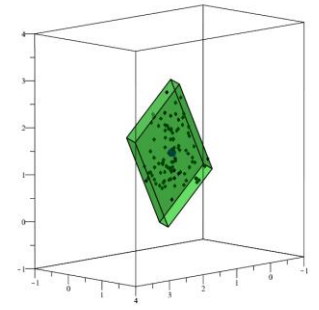
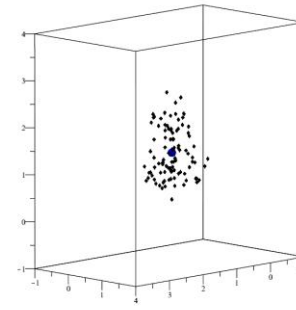
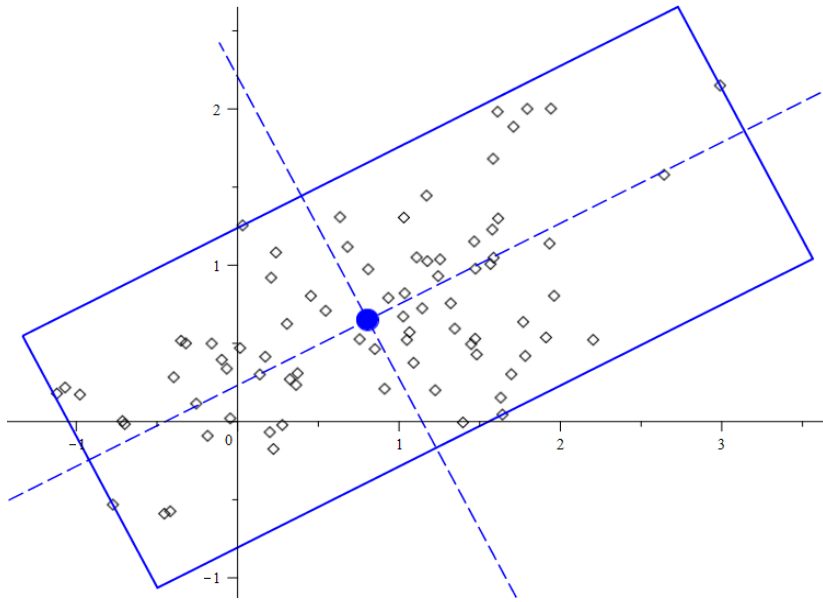
$$\mathbf{C} = \text{cov}(\mathbf{X}, \mathbf{X}) = \frac{1}{N-1} \sum_i \bar{\mathbf{X}}_i \cdot \bar{\mathbf{X}}_i^T$$

- Compute Eigenvectors and Eigenvalues
    - Eigenvectors: Principle components
    - Eigenvalues: Variance

# Principle Component Analysis (PCA)

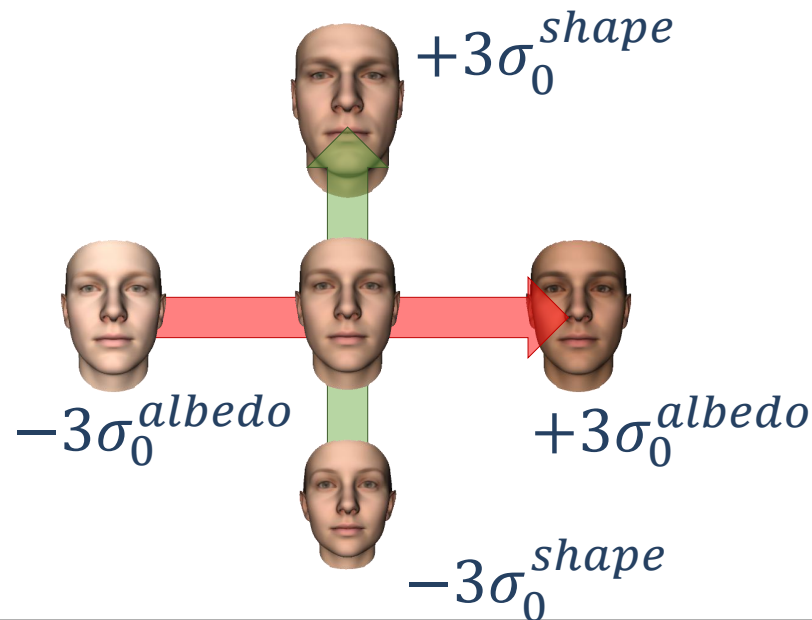
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- Applications:
  - Reduction of dimensionality → approximation
  - Object oriented bounding boxes (OOBB)



# How to Construct a Parametric Face Model?

- Compute face prior:
  - Scan a few hundred faces/expressions and fit a topologically-consistent template to each scan using non-rigid registration
  - **Compute PCA-basis** for identity [and expressions]



Note: the PCA is independently applied to shape and albedo

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- Compute face prior:
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    - New faces can be computed using a linear combination of the basis vectors

$$\mathcal{M}_{\text{geo}}(\boldsymbol{\alpha}, \boldsymbol{\delta}) = \mathbf{a}_{\text{id}} + E_{\text{id}} \cdot \boldsymbol{\alpha} + E_{\text{exp}} \cdot \boldsymbol{\delta}$$

$$\mathcal{M}_{\text{alb}}(\boldsymbol{\beta}) = \mathbf{a}_{\text{alb}} + E_{\text{alb}} \cdot \boldsymbol{\beta}$$

$a_{id}$ : Shape Average

$a_{alb}$ : Albedo Average

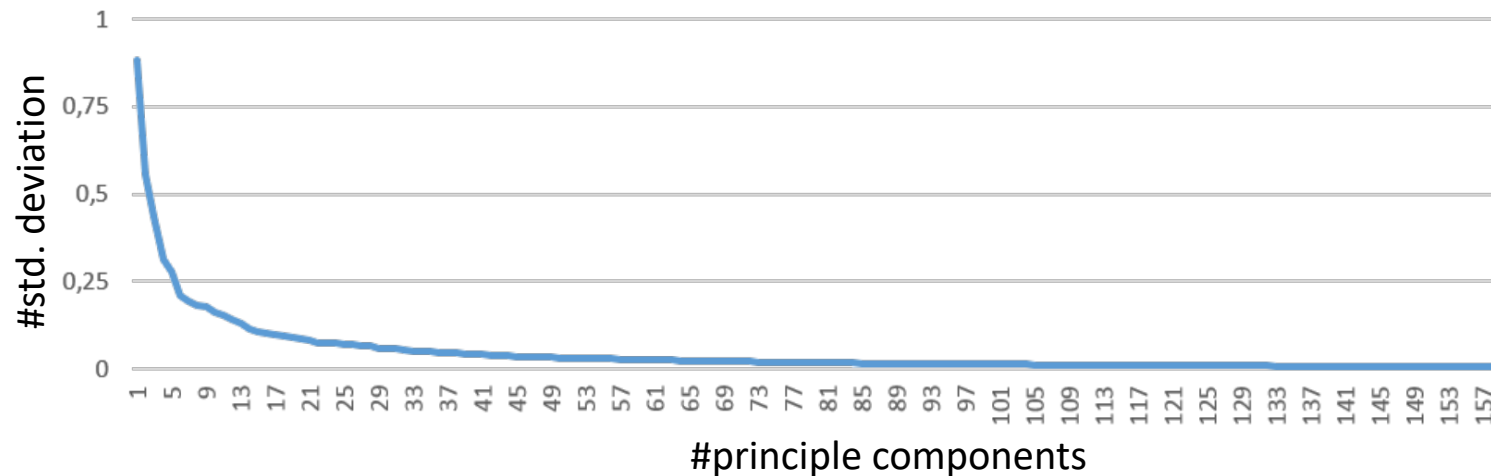
$E_{id}$ : Shape PCA basis

$E_{exp}$ : Expression PCA basis

$E_{alb}$ : Albedo PCA basis

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  - **Compute PCA-basis** for identity [and expressions]
    - New faces can be computed using a linear combination of the PCA basis



Std. deviation drops quickly  
➤ Use this property to reduce computation time (e.g., only use the first 80 principle components)

# How to Construct a Parametric Face Model?

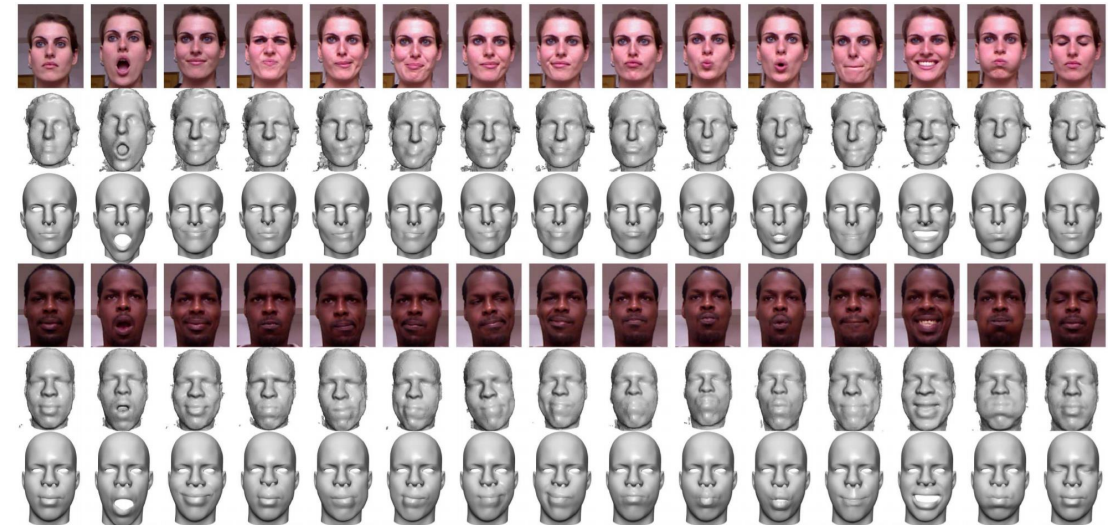
- Expressions:





# How to Construct a Parametric Face Model?

- Expressions:
  - PCA basis representation:
    - Loss of semantic meaning
    - Can be used to compress the data
  - Delta-Blendshape basis:
    - Delta-Blendshape: vertex displacement of a specific expression to the neutral face
    - Use linear combination to interpolate between expressions (same as for PCA)
    - Keeps semantic meaning
      - can be used to transfer expressions to another Blendshape model





# How to Construct a Parametric Face Model?

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  - **Compute PCA-basis** for identity [and expressions]
    - New faces can be computed using a linear combination of the basis vectors

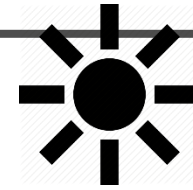
$$\mathcal{M}_{\text{geo}}(\boldsymbol{\alpha}, \boldsymbol{\delta}) = \mathbf{a}_{\text{id}} + E_{\text{id}} \cdot \boldsymbol{\alpha} + E_{\text{exp}} \cdot \boldsymbol{\delta}$$

$$\mathcal{M}_{\text{alb}}(\boldsymbol{\beta}) = \mathbf{a}_{\text{alb}} + E_{\text{alb}} \cdot \boldsymbol{\beta}$$

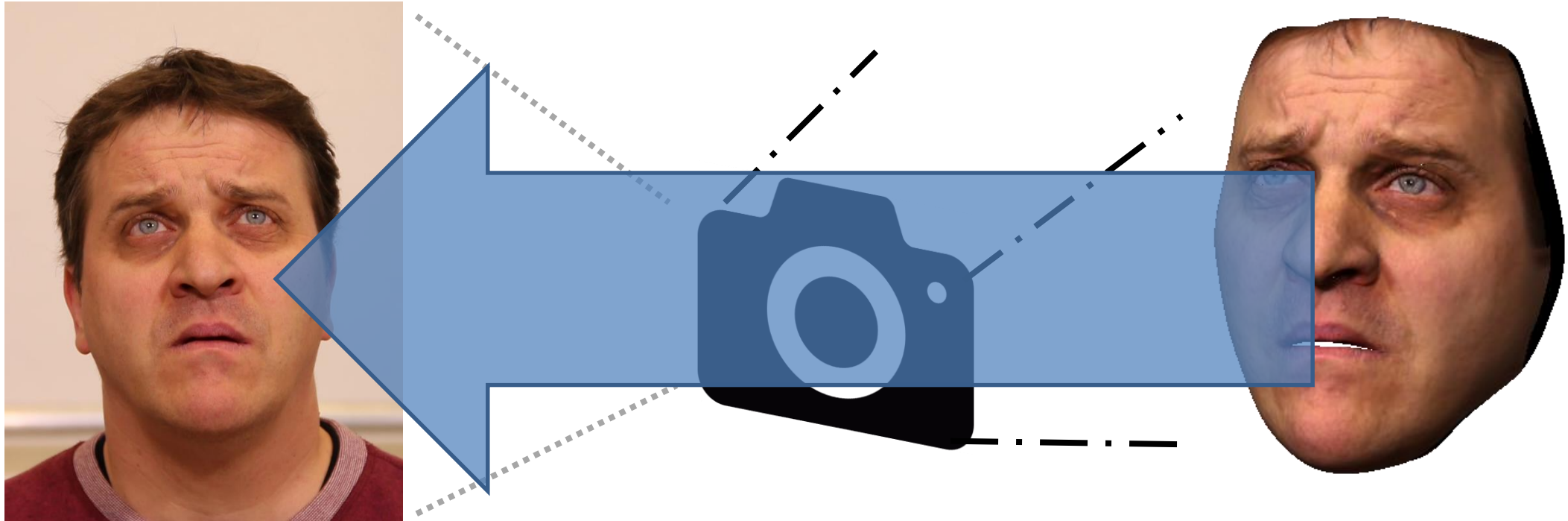
- At runtime: fit prior to input data
  - Estimate coefficients of the linear combination ( $\alpha$ ,  $\beta$ , and  $\delta$ )

# Image Formation Model

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Light Source

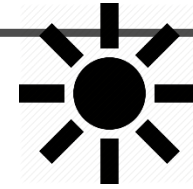


2D Image

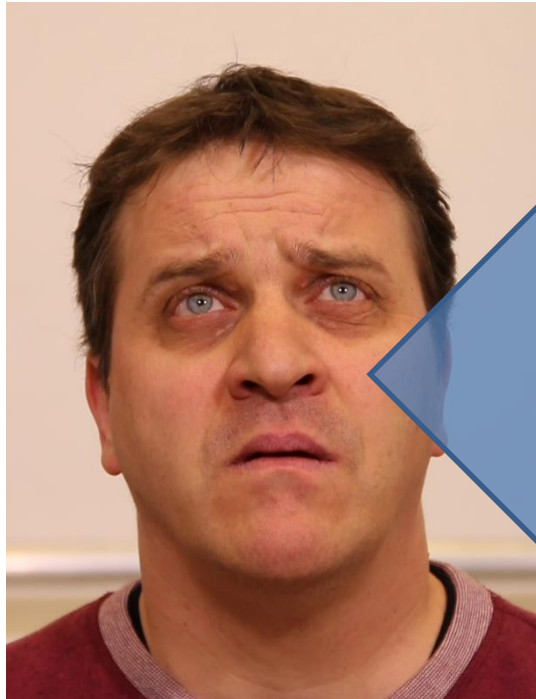
Camera

3D Face

# Image Formation Model



Light Source



2D Image

$$P = (\Phi, \alpha, \beta, \gamma, \delta)$$

Diagram illustrating the parameters of the Image Formation Model  $P$ . The parameters are represented by icons above the equation, with arrows pointing to their corresponding labels below:

- $\Phi$  (pose): Represented by a head in profile.
- $\alpha$  (shape): Represented by a neutral face.
- $\beta$  (albedo): Represented by a face with a color gradient.
- $\gamma$  (illumination): Represented by a color gradient circle.
- $\delta$  (expression): Represented by a face with an open mouth.

Camera



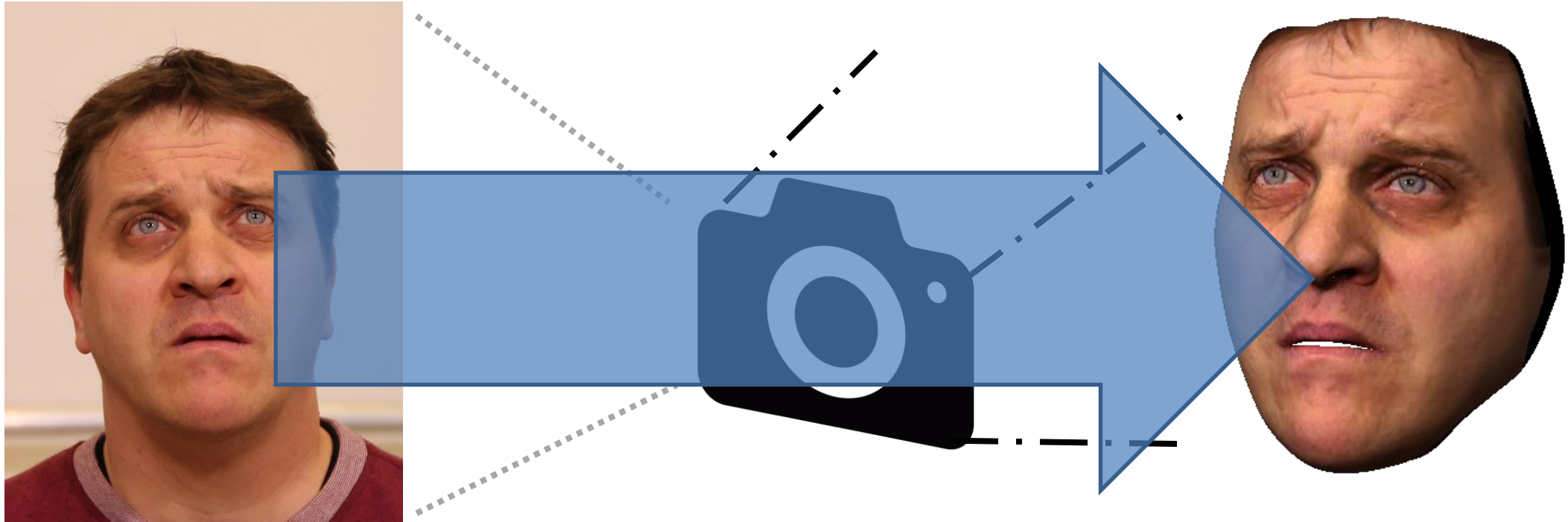
3D Face

# Next Lecture: Face Reconstruction

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Light Source



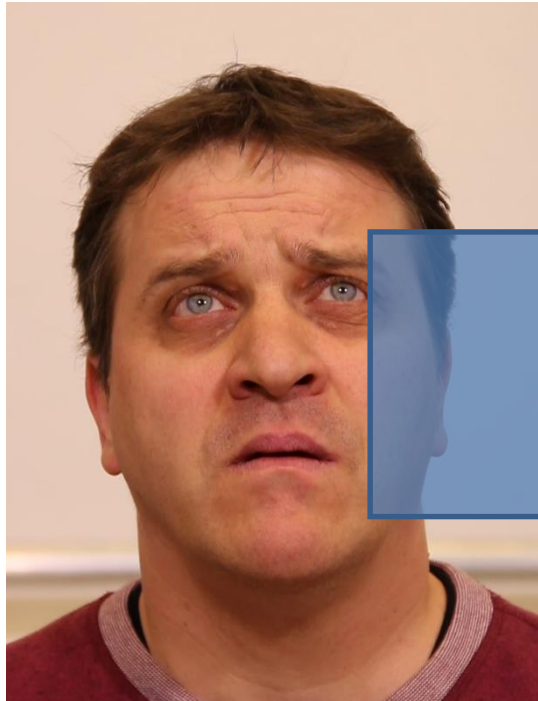
2D Image

Camera

3D Face

# Next Lecture: Face Reconstruction

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2D Image

$$P = (\Phi, \alpha, \beta, \gamma, \delta)$$

Diagram illustrating the parameters of face reconstruction  $P$ :

- $\Phi$  (pose): Represented by a 3D head model tilted at an angle.
- $\alpha$  (shape): Represented by a 3D head model with a neutral expression.
- $\beta$  (albedo): Represented by a 3D head model with a uniform skin tone.
- $\gamma$  (illumination): Represented by a color gradient sphere.
- $\delta$  (expression): Represented by a 3D head model with an open mouth.

# Administrative

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- Reading Homework:
  - [Blanz and Vetter 99] A Morphable Model For The Synthesis Of 3D Faces  
<https://dl.acm.org/doi/pdf/10.1145/311535.311556>
  - Read up on PCA – understand the correlations to SVD and Covariance Matrices
- Next week:
  - Face Tracking & Reconstruction

# Administrative

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See you next week!