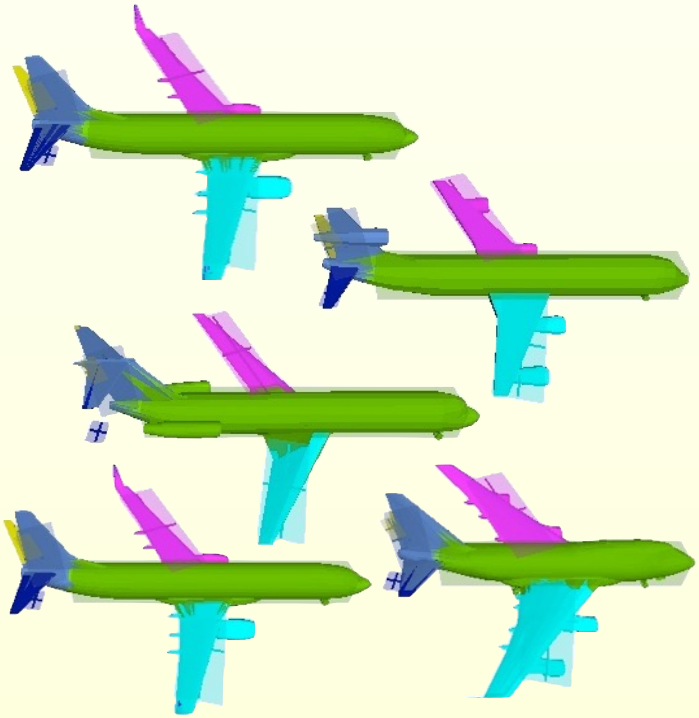
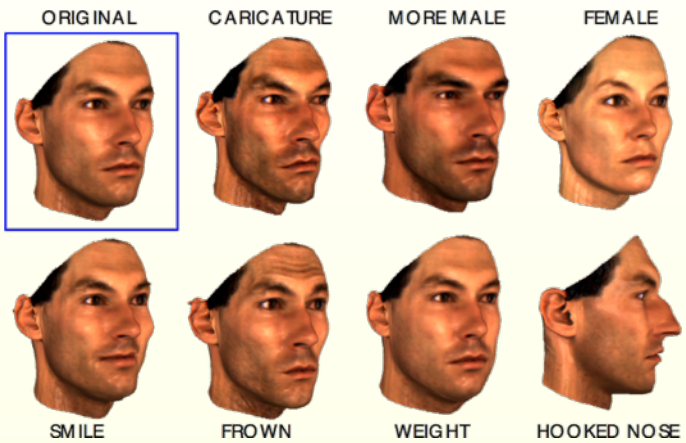
Shape modeling and synthesis

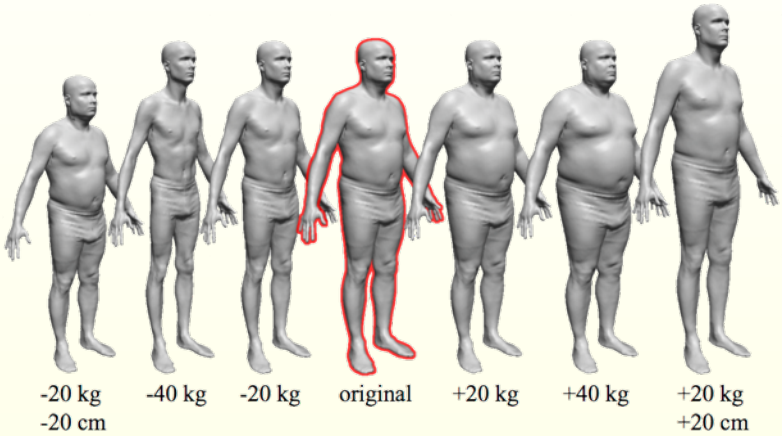


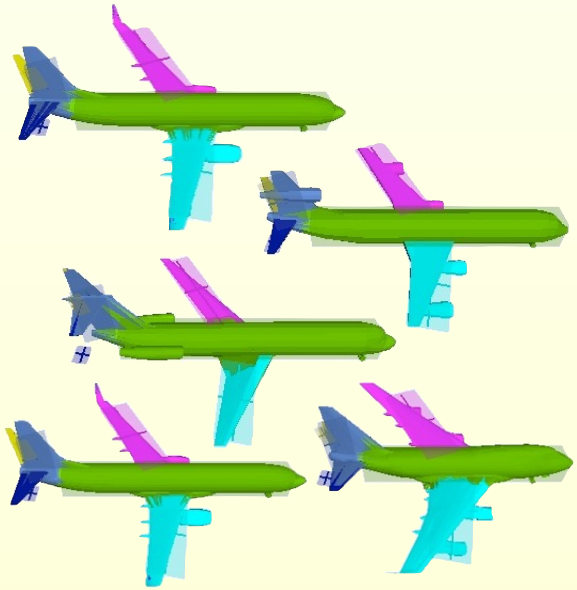
Anastasia Dubrovina
Computer Science Dept.
Stanford University

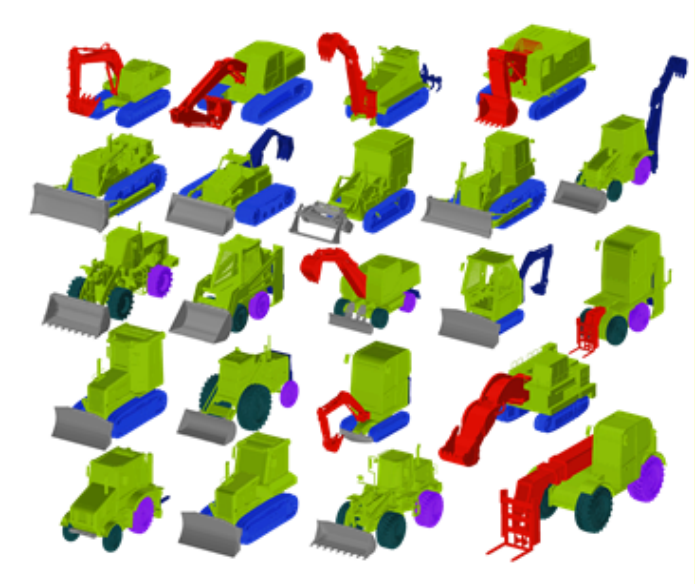
Slides credits: V. Kim, E. Kalogerakis

Topics of today's lecture









Lecture outline

- Morphable 3D Faces
- Modeling space of human bodies
- Modeling man-made shapes
  - Template-based modeling
  - Probabilistic part-based modeling

MORPHABLE 3D FACES

“A Morphable Model For The Synthesis Of 3D Faces”,
V. Blanz and T. Vetter, 1991.

3D face dataset

- Laser scans of 100 male and 100 female adults
- ~70K vertices
- RGB texture, 8 bit per channel
- Normalized orientation and position in space
- Pre-computed correspondences between all models (using a variant of optic flow)

Image credit: Blanz & Vetter

Morphable 3D face model

- All models represented as
  - vector of spatial coordinates

$$S = (X_1, Y_1, Z_1, X_2, ..., Y_n, Z_n)^T \in \mathbb{R}^{3n}$$

  - vectors of textures

$$T = (R_1, G_1, B_1, R_2, ..., G_n, B_n)^T \in \mathbb{R}^{3n}$$

Morphable 3D face model

- All models represented as
  - vector of spatial coordinates

$$S = (X_1, Y_1, Z_1, X_2, ..., Y_n, Z_n)^T \in \mathbb{R}^{3n}$$

  - vectors of textures

$$T = (R_1, G_1, B_1, R_2, ..., G_n, B_n)^T \in \mathbb{R}^{3n}$$

- A new model can be generated as

$$\mathbf{S}_{mod} = \sum_{i=1}^{m} a_i \mathbf{S}_i \,, \quad \mathbf{T}_{mod} = \sum_{i=1}^{m} b_i \mathbf{T}_i \,, \quad \sum_{i=1}^{m} a_i = \sum_{i=1}^{m} b_i = 1$$

Can work, but we'll use another parameterization - see next slide

PCA for model parameterization

- Compute average shape $\overline{S}$ and texture $\overline{T}$, and differences

$$\Delta S_i = S_i - \overline{S} \text{ and } \Delta T_i = T_i - \overline{T}.$$

- Compute PCA over the differences

- New model representation

$$S_{model} = \overline{S} + \sum_{i=1}^{m-1} \alpha_i s_i \,, \quad T_{model} = \overline{T} + \sum_{i=1}^{m-1} \beta_i t_i$$

Eigenvectors of covariance matrices, corresponding to eigenvalues σ_i^S, σ_i^T

Model plausibility

- Measure likelihood of face generated by a set of coefficients using normal distributions

$$p(\vec{\alpha}) \sim exp[-\frac{1}{2}\sum_{i=1}^{m-1}(\alpha_i/\sigma_i)^2]$$

- To increase expressiveness, divide face into sub-regions, and morph them independently

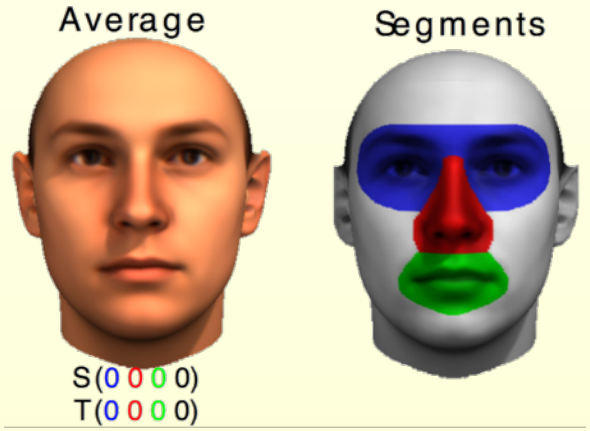


Image credit: Blanz & Vetter

Relating facial attributes to model parameters

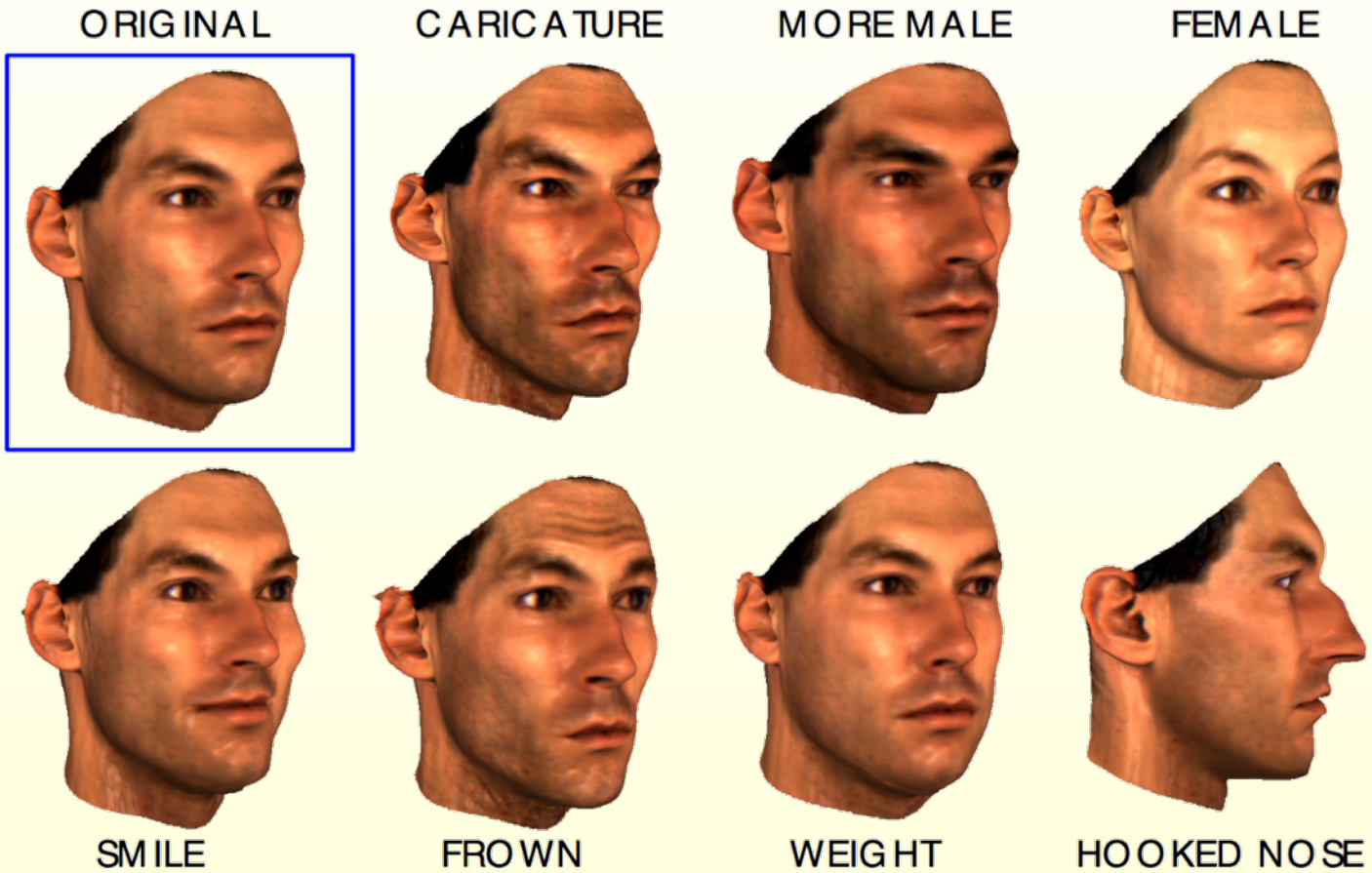


Image credit: Blanz & Vetter

Relating facial attributes to model parameters

- Possible attributes: gender, fullness of faces, dark- ness of eyebrows, double chins, and hooked versus concave noses, etc.
- Given a set of faces with manually assigned attribute strength μ_i, compute weighted differences

$$\Delta S = \sum_{i=1}^{m} \mu_i (S_i - \overline{S}), \quad \Delta T = \sum_{i=1}^{m} \mu_i (T_i - \overline{T})$$

- Change attribute of a new face = add a multiple of $(\Delta S, \Delta T)$

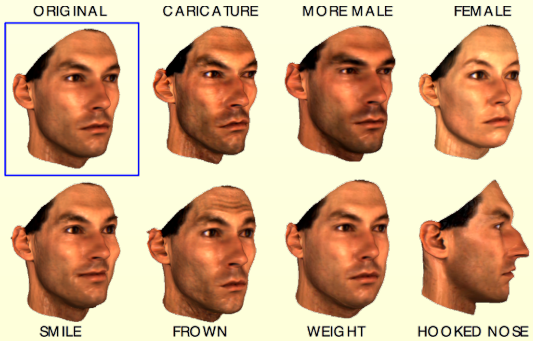


Image credit: Blanz & Vetter

Matching a morphable face to images

- The pipeline:

- Analysis-by-synthesis loop:
  1. Initialize: $\overline{S}$, $\overline{T}$; camera pose, ambient and directed light estimated by user
  2. Render using current parameters
  3. Update parameters according to residual differences
  4. Repeat until convergence
  5. Followed by illumination-corrected texture extraction
- Computation time ~50 minutes

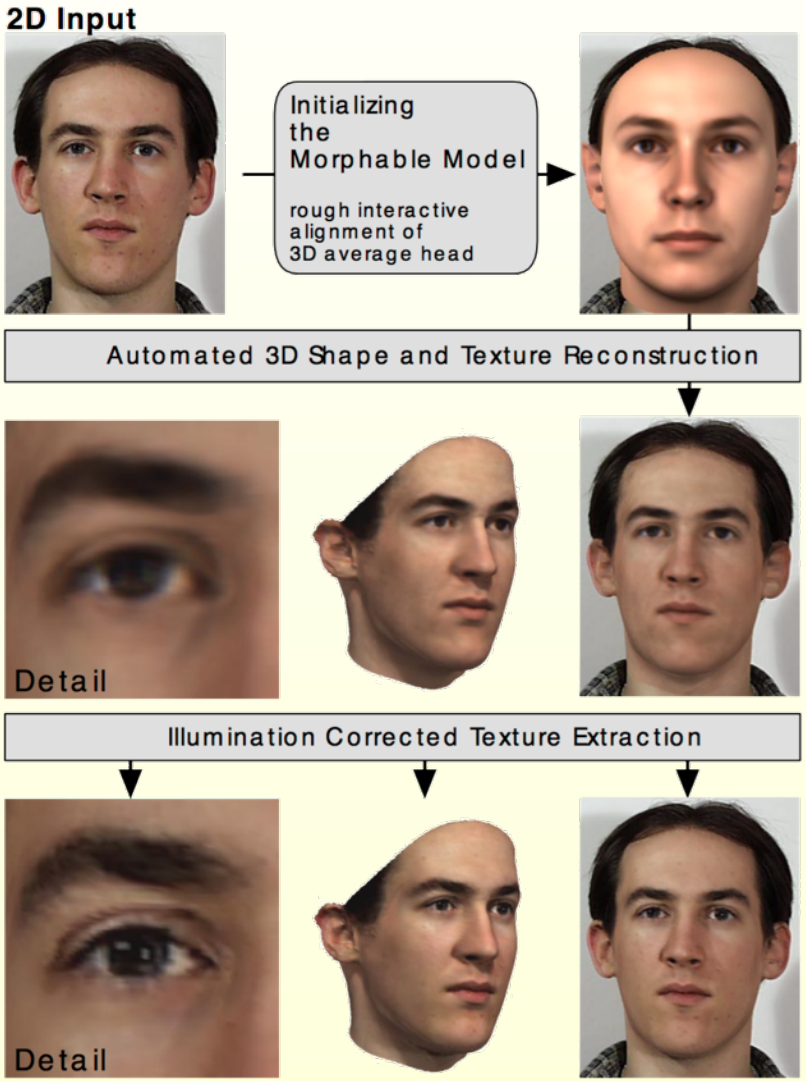


Image credit: Blanz & Vetter

A Morphable Model for the Synthesis of 3D Faces

Volker Blanz & Thomas Vetter

MPI for Biological Cybernetics
Tübingen, Germany

MODELING SPACE OF HUMAN BODIES

Approaches

- Model body shape variations
  - “The space of human body shapes: reconstruction and parameterization from range scans,” B. Allen et al., 2003

- Model shape and pose variations
  - “SCAPE: Shape Completion and Animation of People,” Angelov et al., 2005

Variance in human bodies

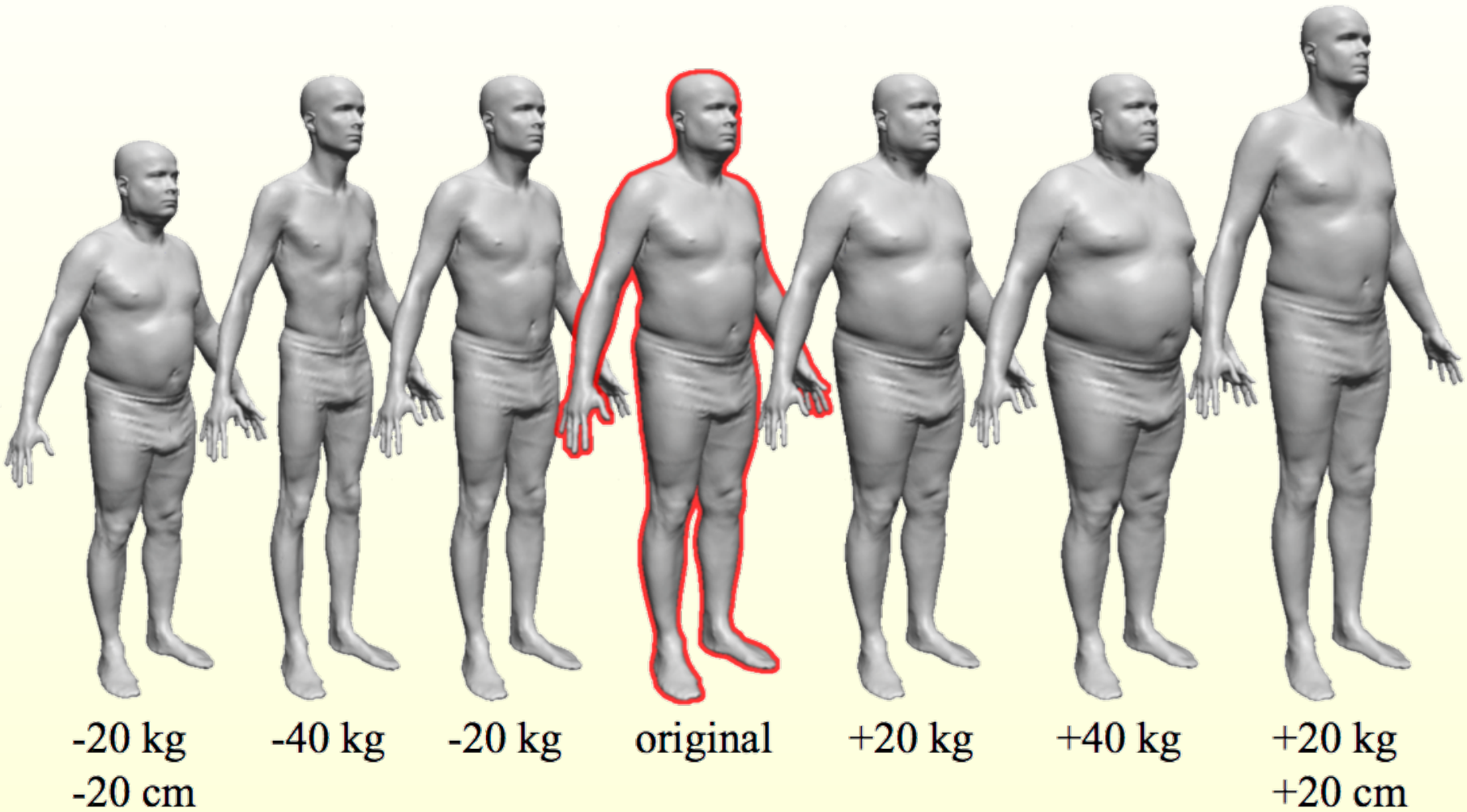
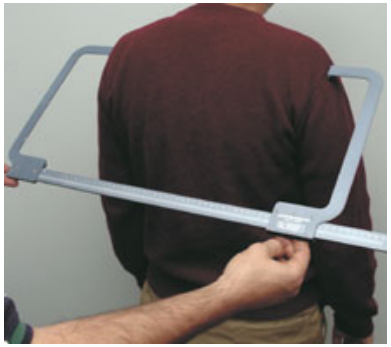


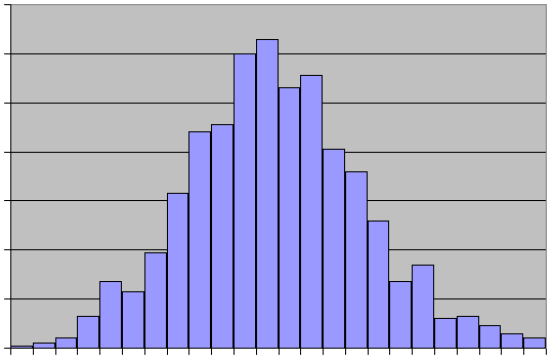
Image credit: Bl. Allen

Variance in human bodies



Traditional anthropometry

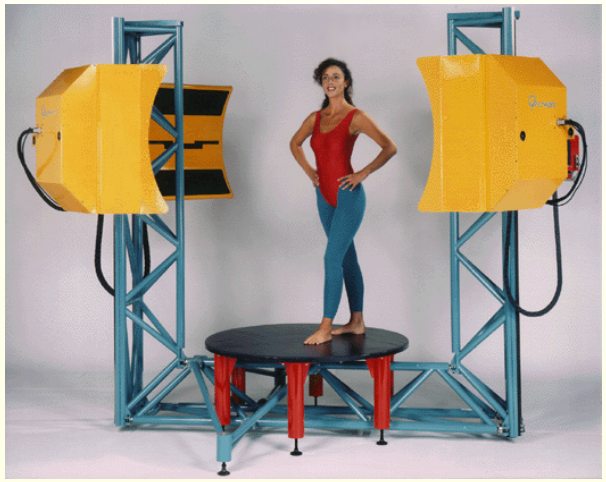
Subject Number	Neck Base Circumference (mm)	Shoulder Breadth (mm)	Sitting Height (mm)	Stature (mm)	Sul Ski (mr
1	537.00	647.00	971.00	1872.00	
2	496.00	529.00	962.00	1829.00	
7	475.00	547.00	936.00	1731.00	
8	456.00	477.00	935.00	1828.00	
9	481.00	512.00	926.00	1762.00	
10	486.00	519.00	950.00	1806.00	
12	465.00	495.00	924.00	1702.00	
13	443.00	452.00	866.00	1705.00	
16	459.00	493.00	936.00	1836.00	
24	480.00	519.00	940.00	1771.00	
25	481.00	539.00	941.00	1829.00	
26	484.00	539.00	894.00	1704.00	
27	450.00	489.00	884.00	1712.00	



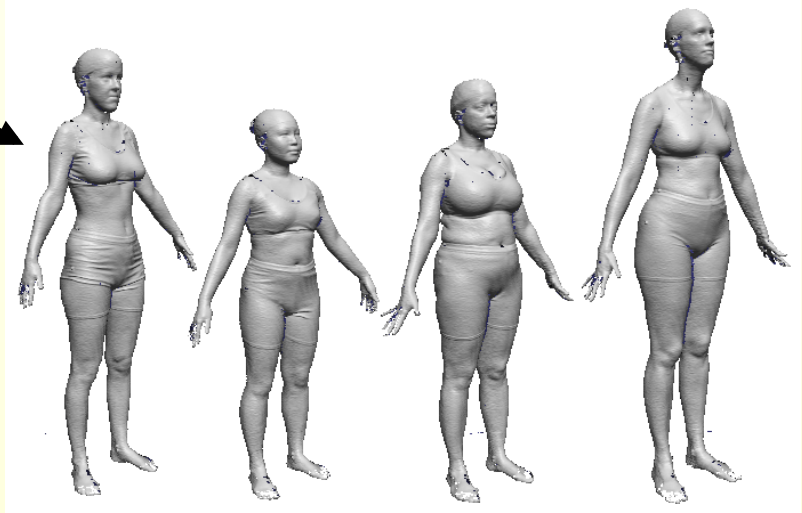
Slide credit: V. Kim

Variance in human bodies

Leverage new technology



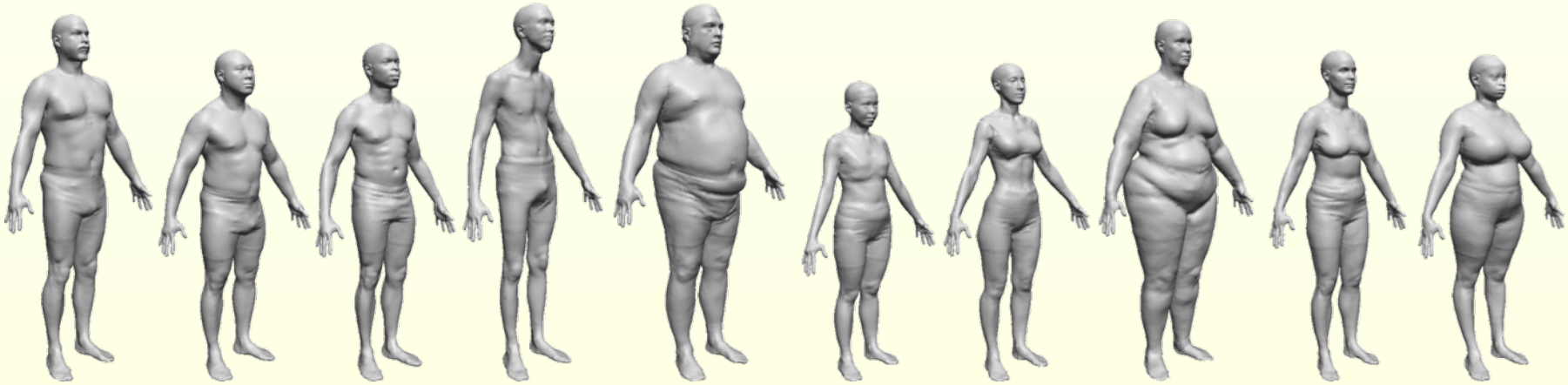
Cyberware 3D whole body scanner



Slide credit: V. Kim

Modeling the space of human bodies

- “The space of human body shapes: reconstruction and parameterization from range scans,” B. Allen et al., 2003.

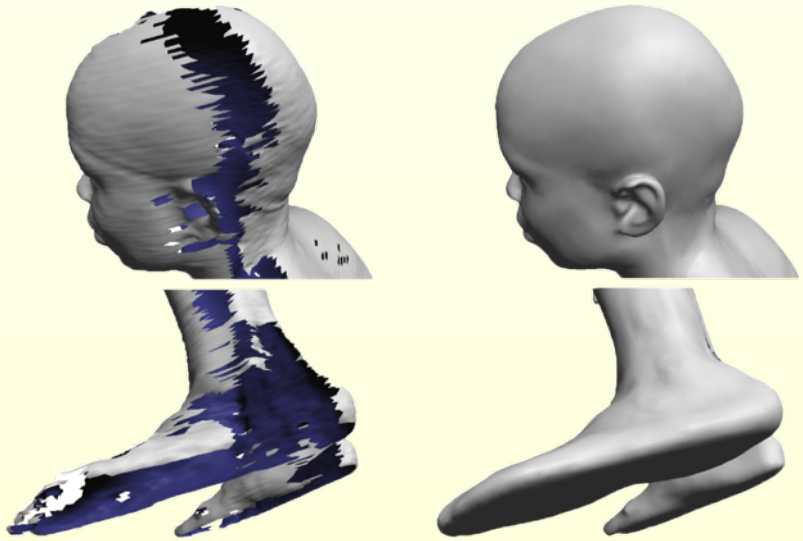


The dataset: the Civilian American and European Surface Anthropometry Resource Project (CAESAR)

Image credit: B. Allen

Data set

- 74 white markers were placed on the subject at anthropometric landmarks
- demographic data such as age, weight, and ethnic group were recorded
- 125 male and 125 female scans



Hole filling

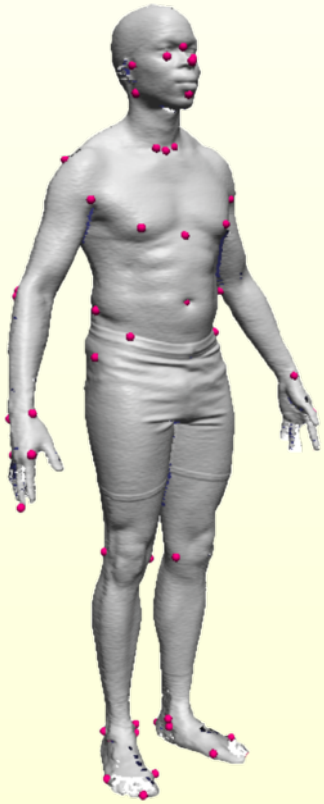


Image credit: B. Allen

Data alignment - scan parameterization

- Fit a scanned surface $\mathcal{D}$ to a template surface

- Affine transformation per vertex $\mathbf{T}_i$
- Objective function

$$E = \alpha E_d + \beta E_s + \gamma E_m$$

Data error: template and target surfaces as close as possible

$$E_d = \sum_{i=1}^{n} w_i \, \mathrm{dist}^2(\mathbf{T}_i \mathbf{v}_i, \mathcal{D})$$

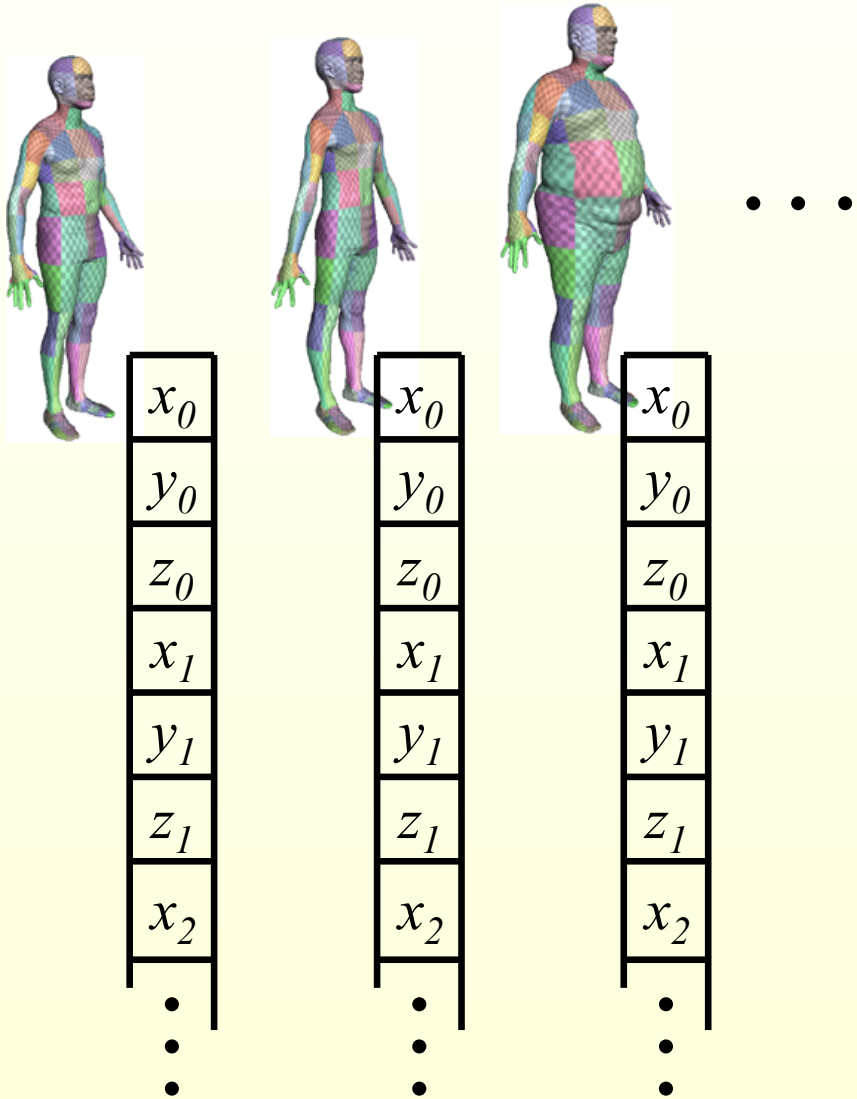
Transformation smoothness

$$E_s = \sum_{\{i,j|\{\mathbf{v}_i,\mathbf{v}_j\}\in edges(\mathcal{T})\}} ||\mathbf{T}_i - \mathbf{T}_j||_F^2$$

Marker error $$E_m = \sum_{i=1}^{m} ||\mathbf{T}_{\kappa_i} \mathbf{v}_{\kappa_i} - \mathbf{m}_i||^2$$

Image credit: B. Allen

Variance in human bodies

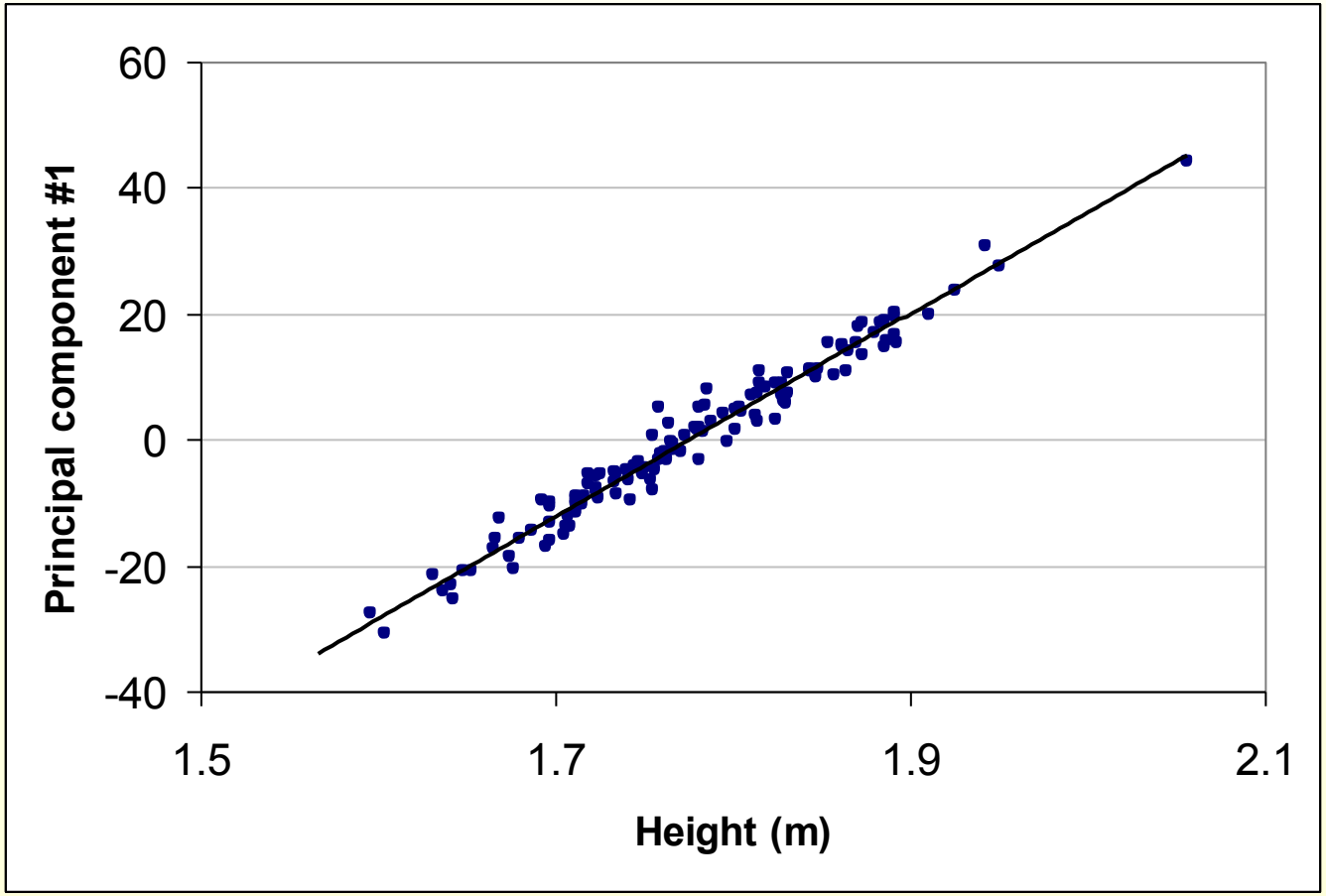


Statistical analysis (PCA) on vertex positions

average male

Slide credit: V. Kim

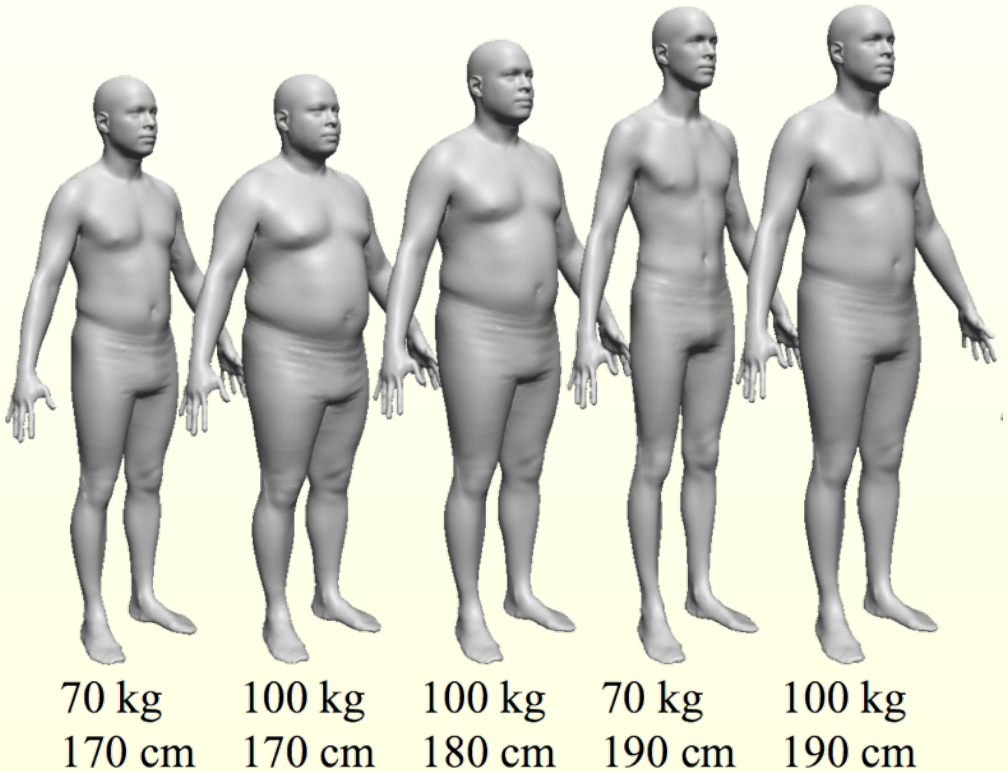
Variance in human bodies



Slide credit: V. Kim

Applications

- Feature-based synthesis



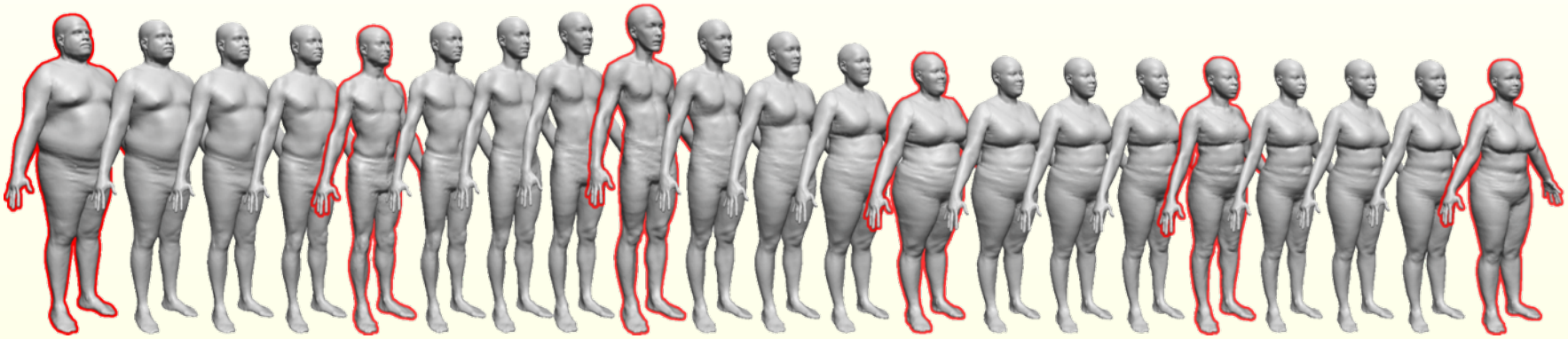
- Learned mapping between controls and PCA coefficients

$$\mathbf{M}\begin{bmatrix} f_1 & \cdots & f_l & 1 \end{bmatrix}^{\mathrm{T}} = \mathbf{p}$$

Image credit: B. Allen

Applications

- Morphing



- Skeleton transfer

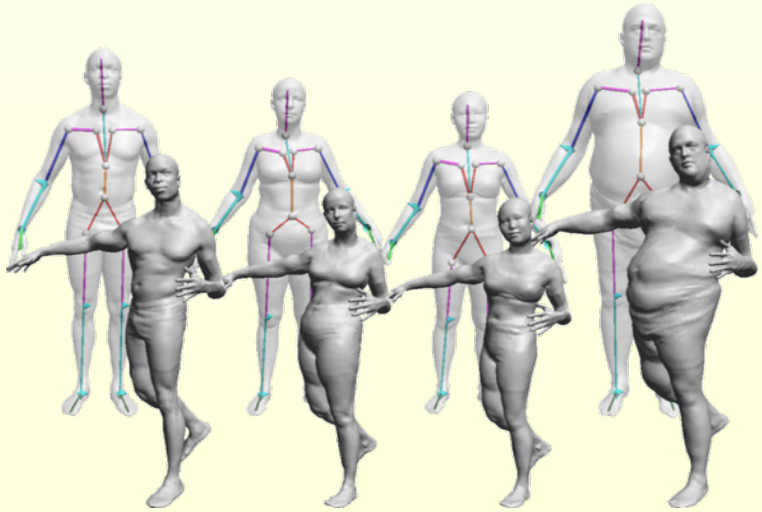


Image credit: B. Allen

SCAPE: Shape Completion and Animation of People

- Previous method: all humans in neutral poses

SCAPE: Shape Completion and Animation of People

- Previous method: all humans in neutral poses

- Next work: “SCAPE: Shape Completion and Animation of People,” Angelov et al., 2005
- Decouples deformation into *rigid and non-rigid* components - body *shape variation model* and *pose deformation model*

- Dataset
  - 70 poses of a particular person in wide variety of poses
  - 37 scans of different people in neutral poses + CAESAR

Mesh processing pipeline

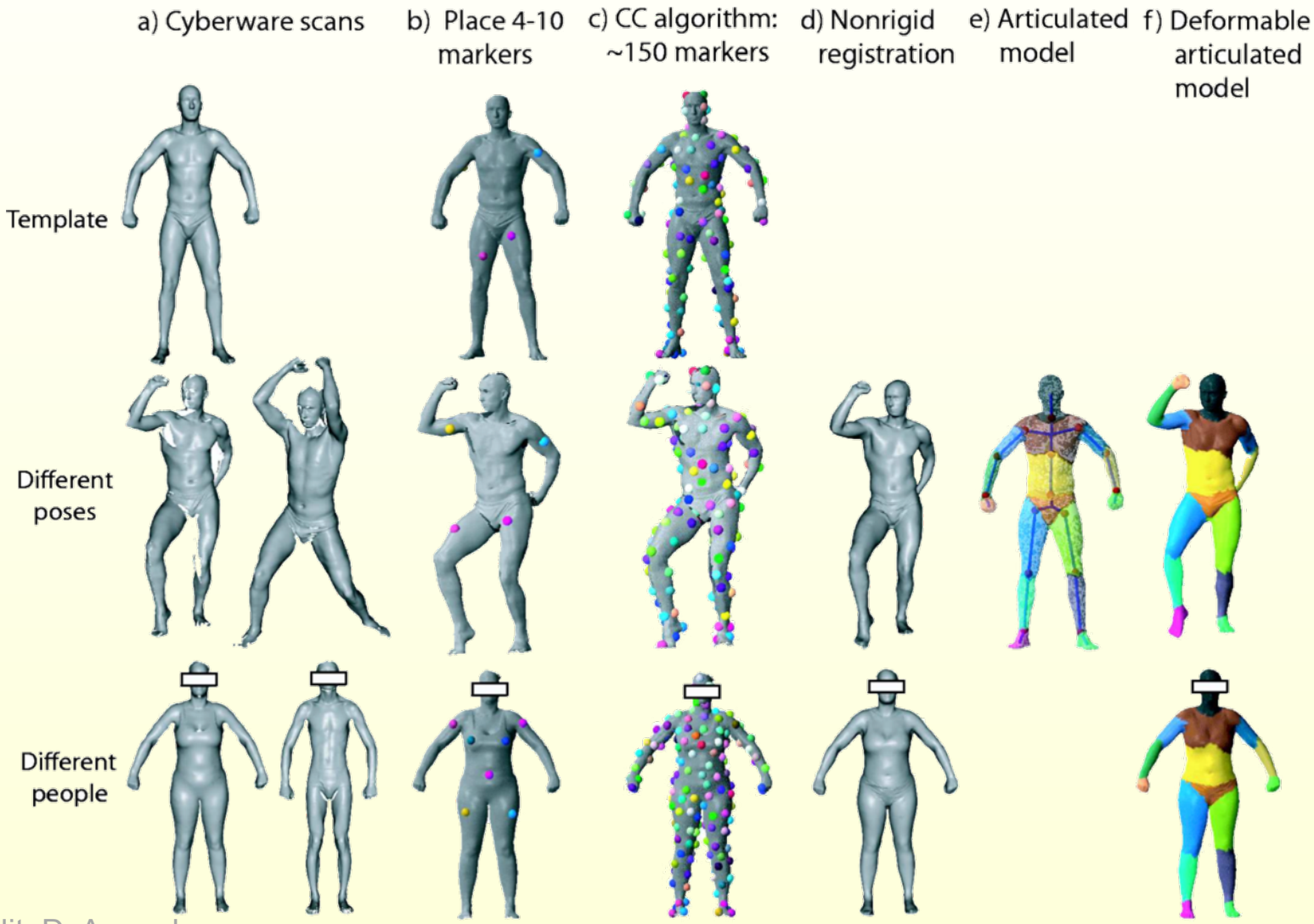


Image credit: D. Anguelov

Pose deformation model

- Factorize into joint rotation R_k^i and triangle transformation Q_k^i

$$\underset{\{Q_1^i,\ldots,Q_P^i\}}{\operatorname{argmin}} \quad \sum_k \sum_{j=2,3} \|R_k^i Q_k^i \hat{v}_{k,j} - v_{k,j}^i\|^2 + \; w_s \sum_{k_1,k_2 \text{ adj}} I(\ell_{k_1} = \ell_{k_2}) \cdot \|Q_{k_1}^i - Q_{k_2}^i\|^2$$

Pose deformation model

- Factorize into joint rotation R_k^i and triangle transformation Q_k^i

$$\underset{\{Q_1^i,\ldots,Q_P^i\}}{\operatorname{argmin}} \quad \sum_k \sum_{j=2,3} \|R_k^i Q_k^i \hat{v}_{k,j} - v_{k,j}^i\|^2 + \; w_s \sum_{k_1,k_2 \text{ adj}} I(\ell_{k_1} = \ell_{k_2}) \cdot \|Q_{k_1}^i - Q_{k_2}^i\|^2$$

- Learn how to <u>predict</u> Q_k^i from the <u>twists of its adjacent joints</u>

Pose deformation model

- Factorize into joint rotation R_k^i and triangle transformation Q_k^i

$$\underset{\{Q_1^i,\ldots,Q_P^i\}}{\operatorname{argmin}} \quad \sum_k \sum_{j=2,3} \|R_k^i Q_k^i \hat{v}_{k,j} - v_{k,j}^i\|^2 + \; w_s \sum_{k_1,k_2 \text{ adj}} I(\ell_{k_1} = \ell_{k_2}) \cdot \|Q_{k_1}^i - Q_{k_2}^i\|^2$$

- Learn how to <u>predict</u> Q_k^i from the <u>twists of its adjacent joints</u>

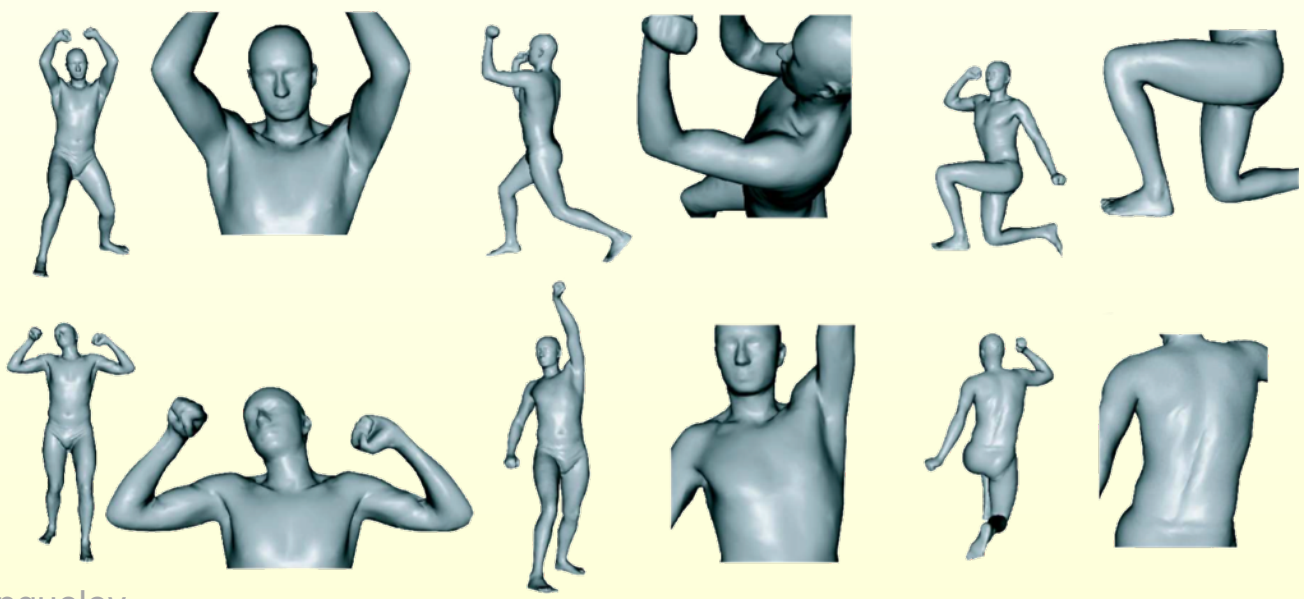


Image credit: D. Anguelov

Body shape deformation model

- Complete deformation model is given by

$$v^i_{k,j} = R^i_{\ell[k]} S^i_k Q^i_k \hat{v}_{k,j}$$

Body shape deformations

Body shape deformation model

- Complete deformation model is given by

$$v^i_{k,j} = R^i_{\ell[k]} S^i_k Q^i_k \hat{v}_{k,j}$$

Body shape deformations

- Model given by PCA $\quad S^i = U\beta^i + \mu$

Covariance matrix eigenvectors and mean transformation

Body shape deformation model

- Complete deformation model is given by

$$v^i_{k,j} = R^i_{\ell[k]} S^i_k Q^i_k \hat{v}_{k,j}$$

Body shape deformations

- Model given by PCA $\quad S^i = U\beta^i + \mu$

Covariance matrix eigenvectors and mean transformation

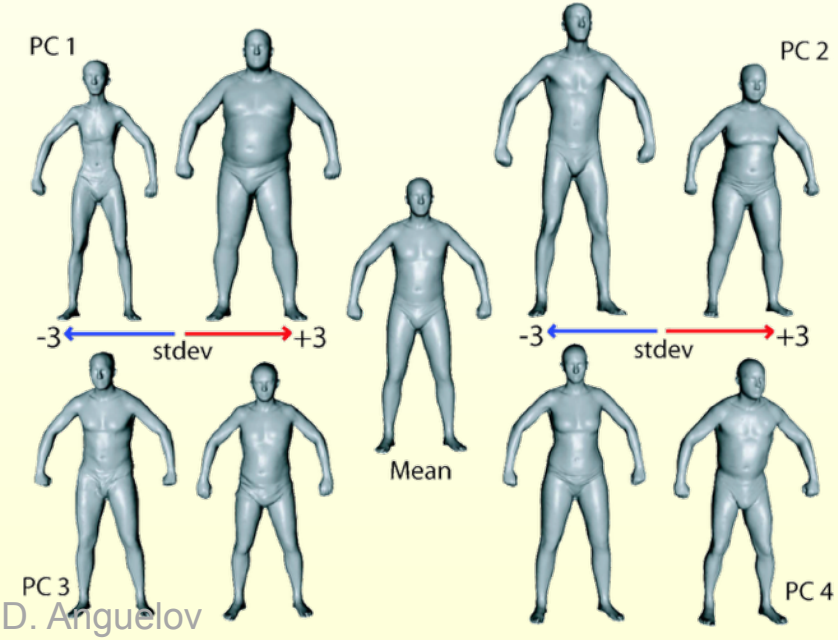


Image credit: D. Anguelov

Shape deformation generation

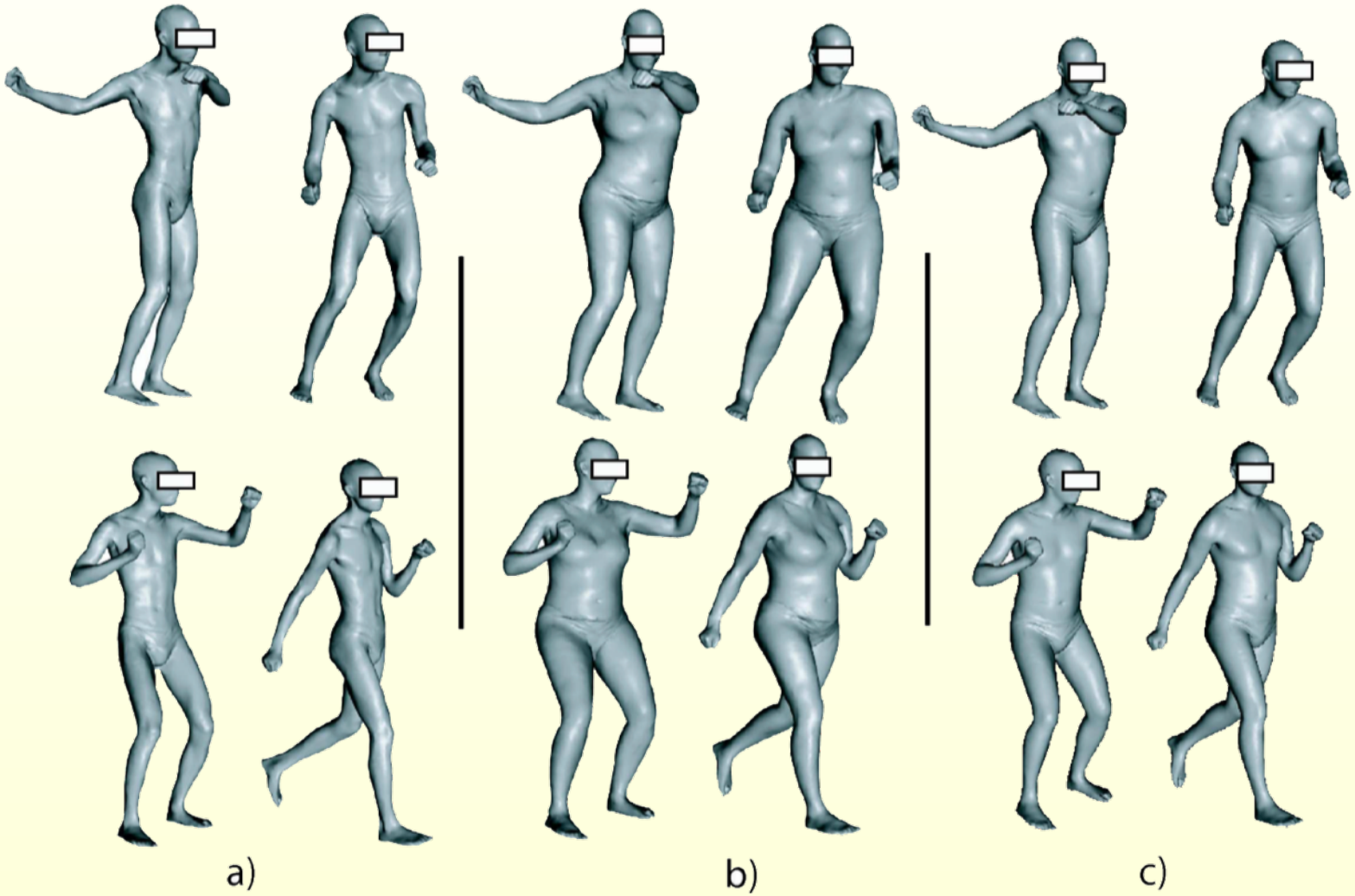
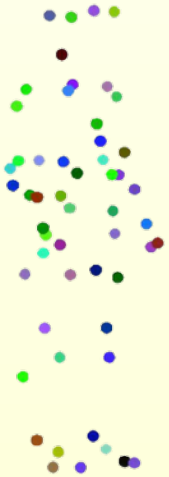


Image credit: D. Anguelov

Motion capture animation

a)



b)

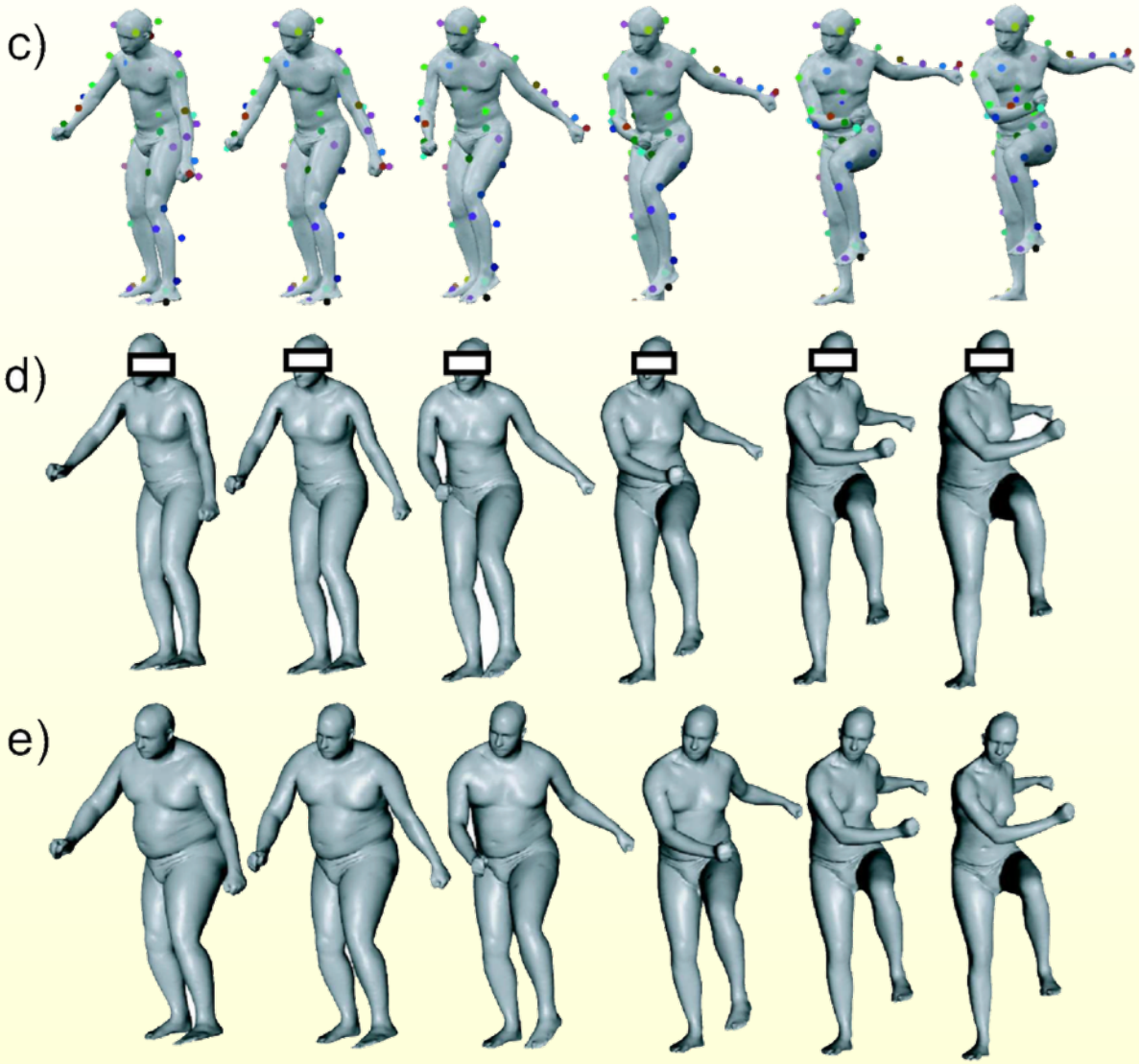


Image credit: D. Anguelov

Motion capture animation

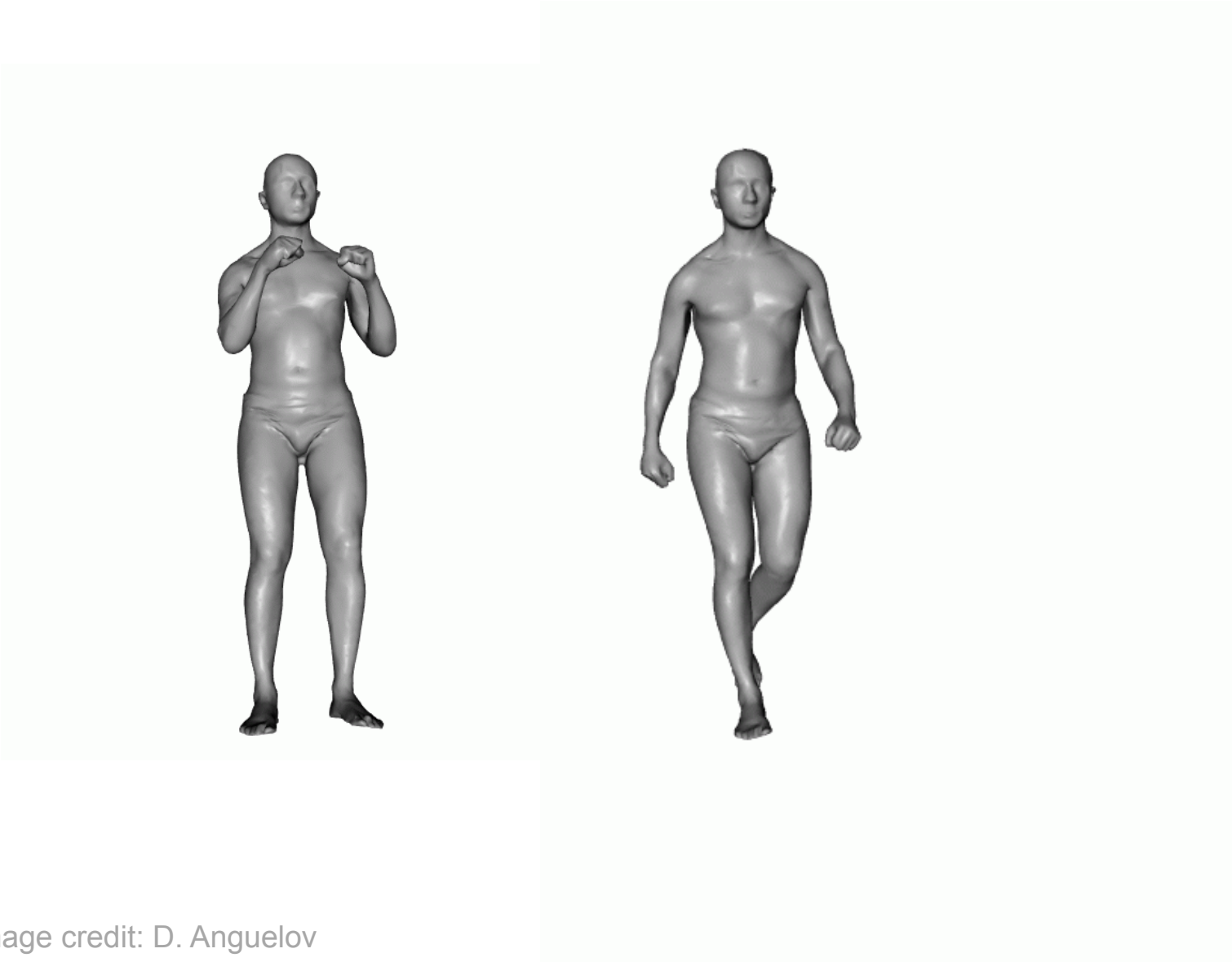


Image credit: D. Anguelov

Further afield

- “A model for pose and body shape,” Hasler et al., 2009
- Suggested *joint* pose and body shape model

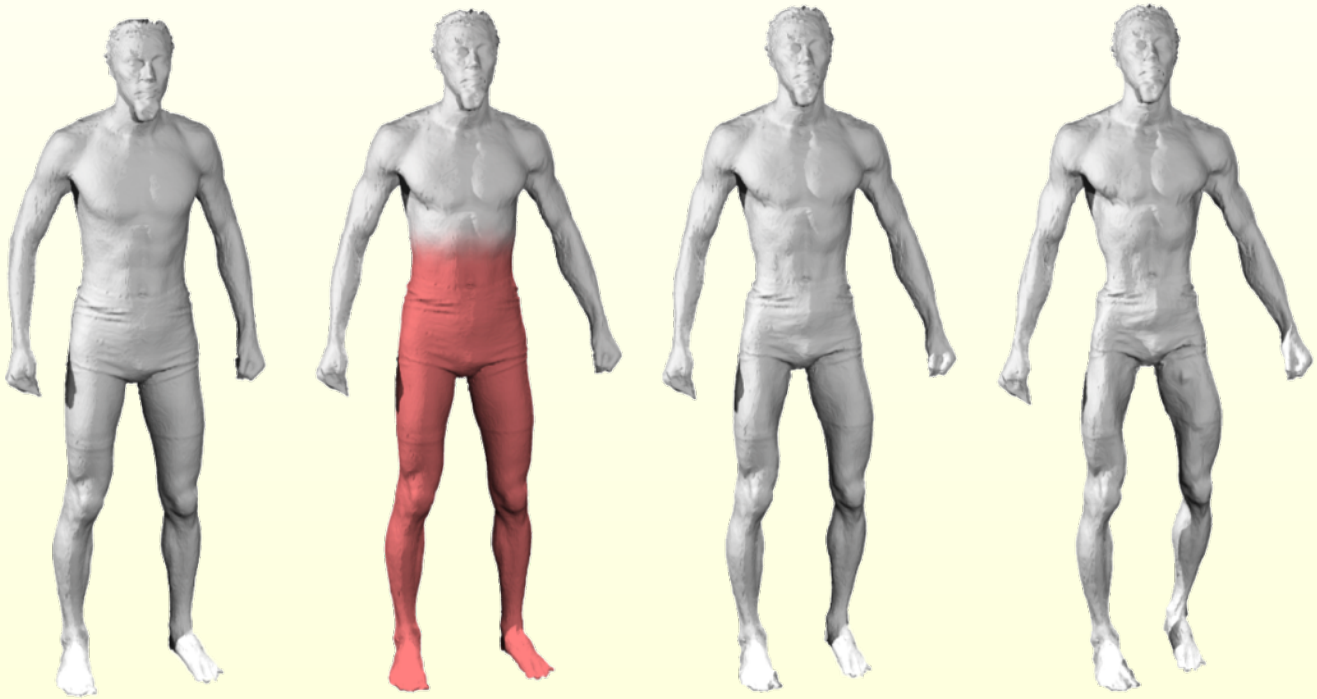
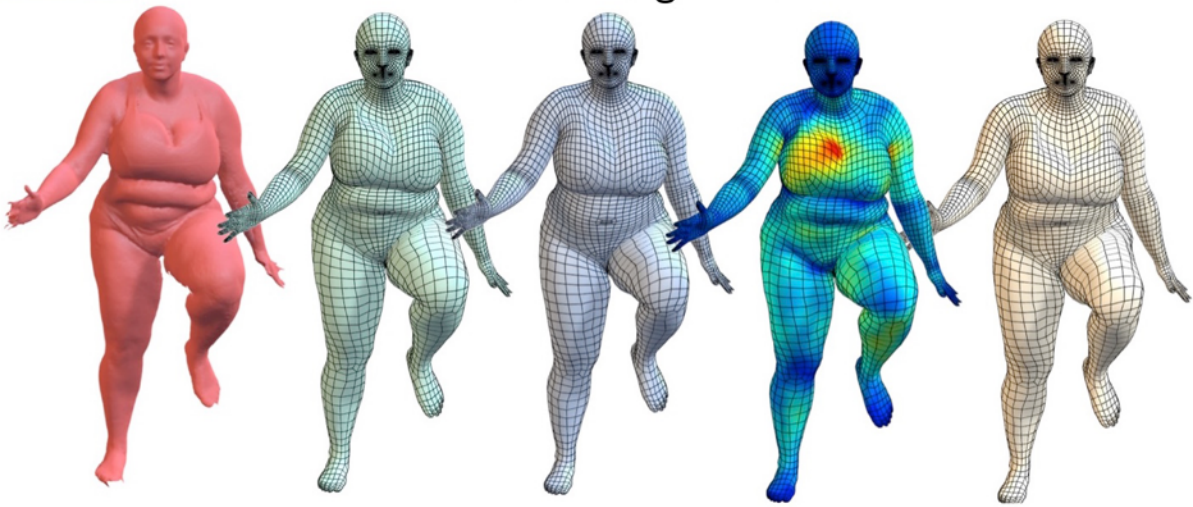


Image credit: https://ps.is.tuebingen.mpg.de/

Further afield: Prof. Michael Black's lab

Breathing model

4D scanner (60 fps)



4D scan 4Cap BlendSCAPE Soft tissue Dyna

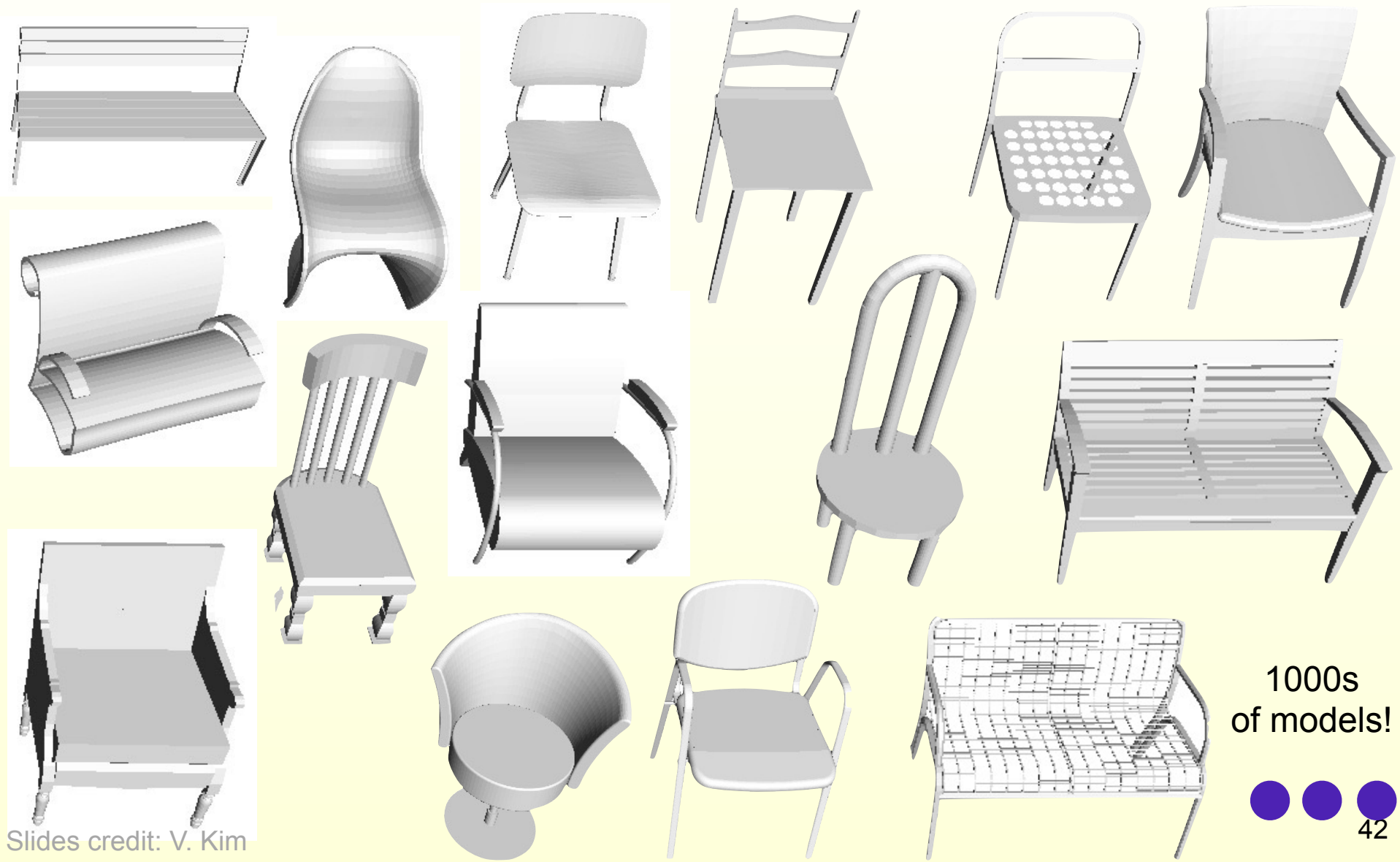
LEARNING TO MODEL MAN-MADE SHAPES

Approaches

- Part-based template learning
  - “Learning Part-based Templates from Large Collections of 3D Shapes,” Kim et al., 2013

- Component-based probabilistic model
  - “A Probabilistic Model for Component-Based Shape Synthesis,” Kalogerakis et al., 2012

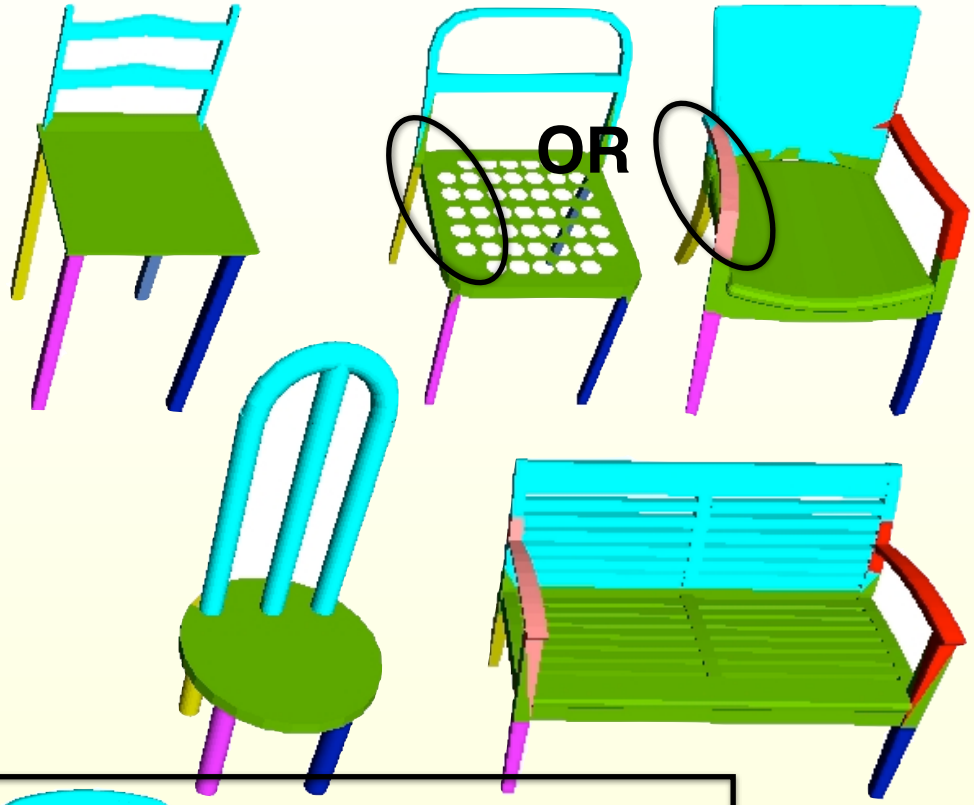
Collections of 3D shapes



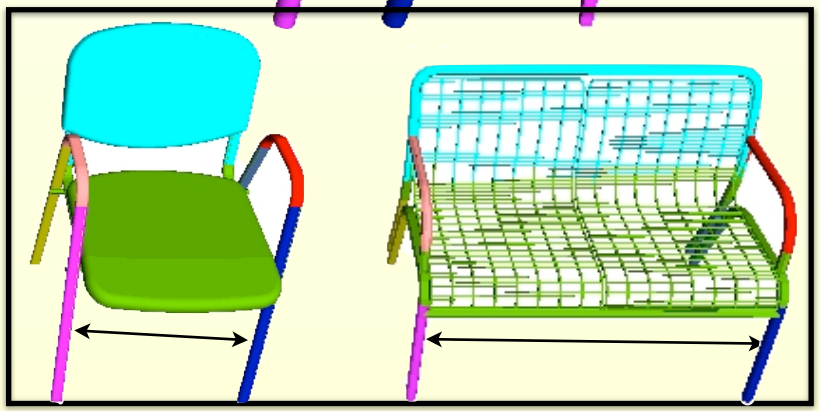
1000s
of models!

Slides credit: V. Kim

Understand Variations



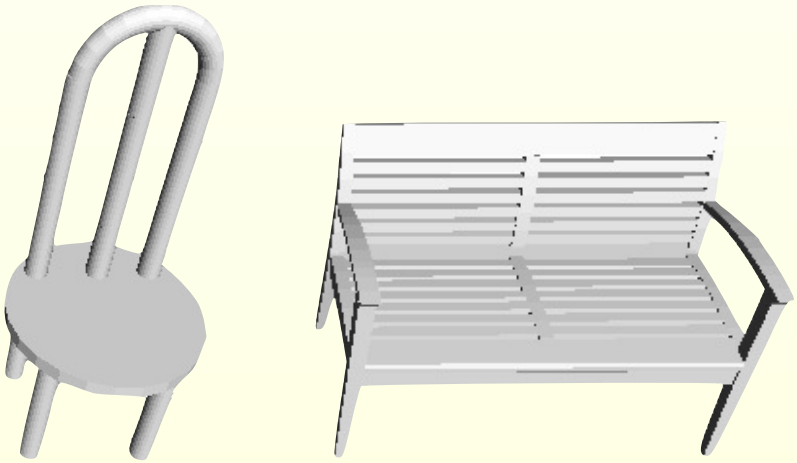
Seats vary in width



1000s of models!

Need Joint Analysis

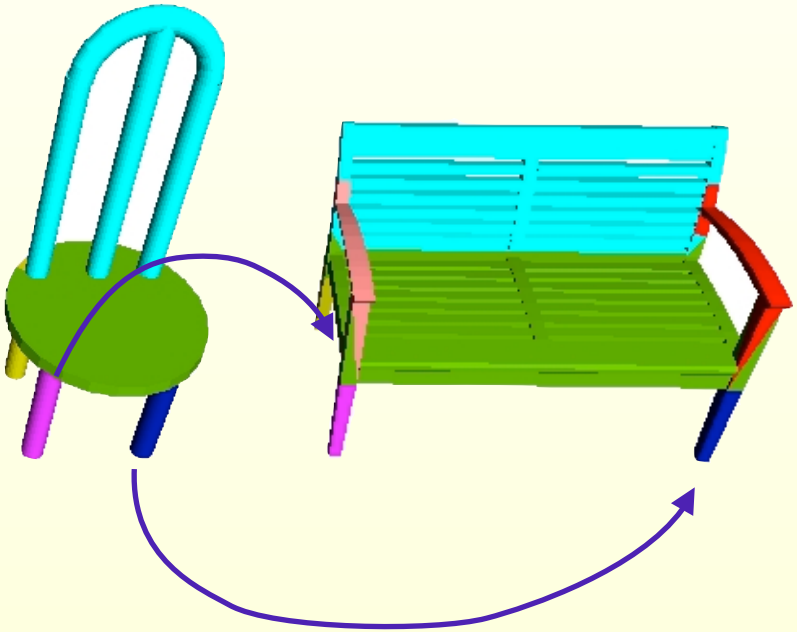
- The problems are inter-related:
  - Correspondences
  - Consistent Segmentations
  - Shape Variations



Slides credit: V. Kim

Need Joint Analysis

- The problems are inter-related:
  - Correspondences
  - Consistent Segmentations
  - Shape Variations

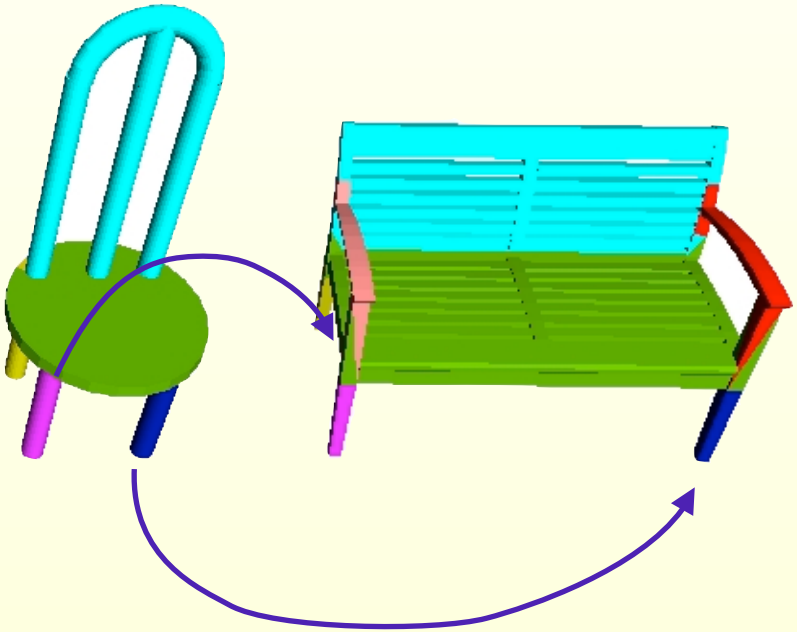


Smaller search space

Slides credit: V. Kim

Need Joint Analysis

- The problems are inter-related:
  - Correspondences
  - Consistent Segmentations
  - Shape Variations

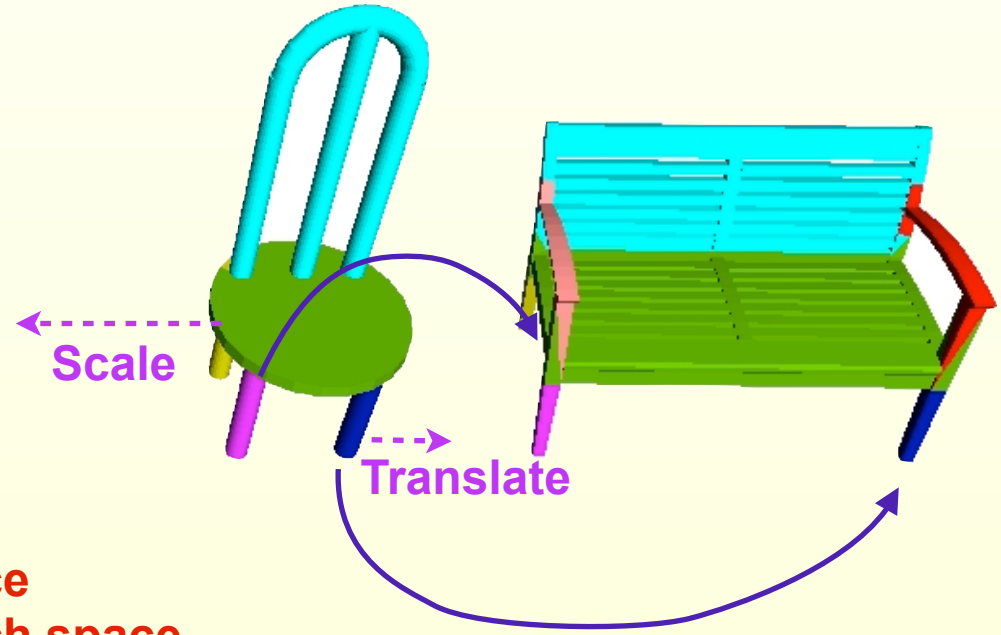


Smaller search space

Slides credit: V. Kim

Need Joint Analysis

- The problems are inter-related:
  - Correspondences
  - Consistent Segmentations
  - Shape Variations

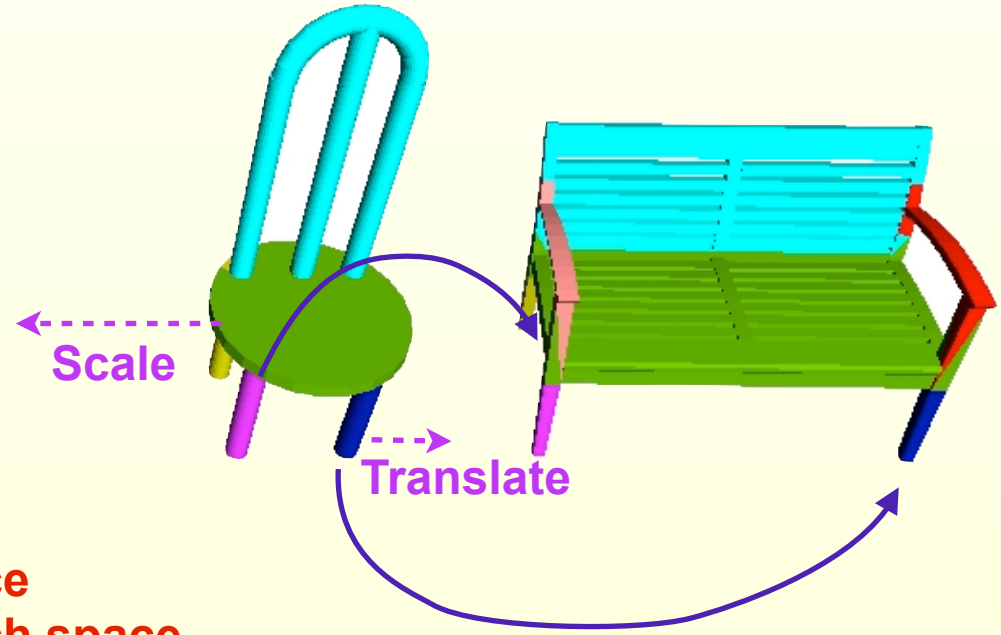


Smaller search space
More accurate search space

Slides credit: V. Kim

Need Joint Analysis

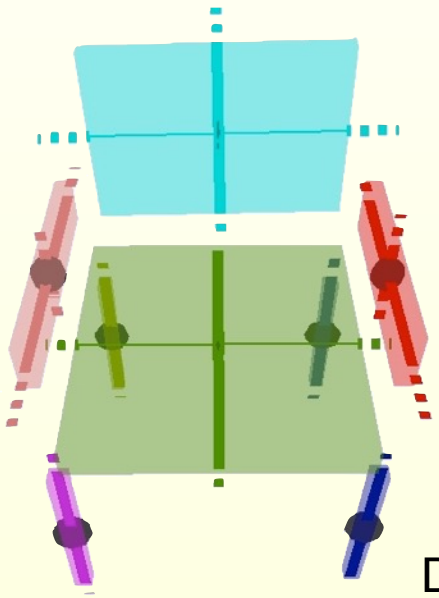
- The problems are inter-related:
  - Correspondences
  - Consistent Segmentations
  - Shape Variations



Smaller search space
More accurate search space
Man-made object vary w.r.t. parts

Slides credit: V. Kim

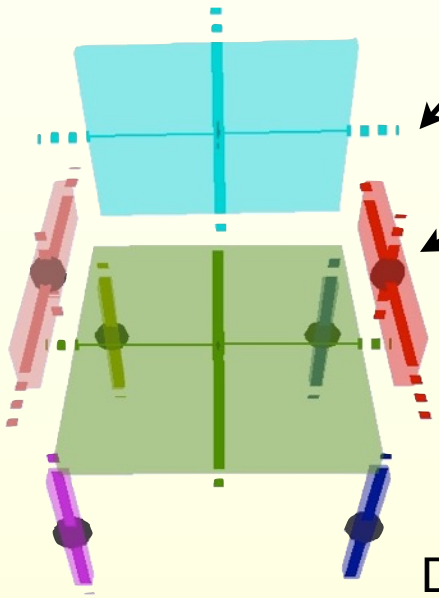
Box-like Templates



Deformable Template

Slides credit: V. Kim

Box-like Templates



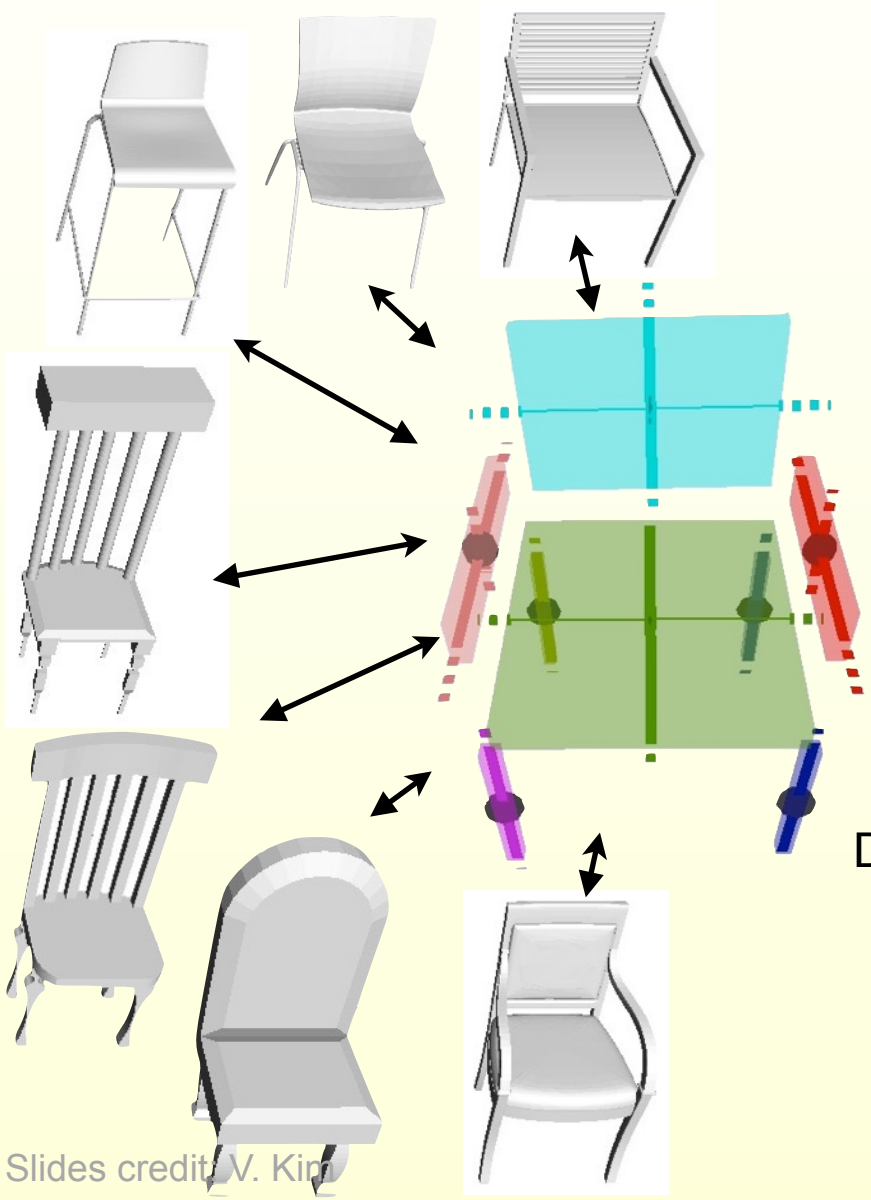
variance in scale

variance in positions

Deformable Template

Slides credit: V. Kim

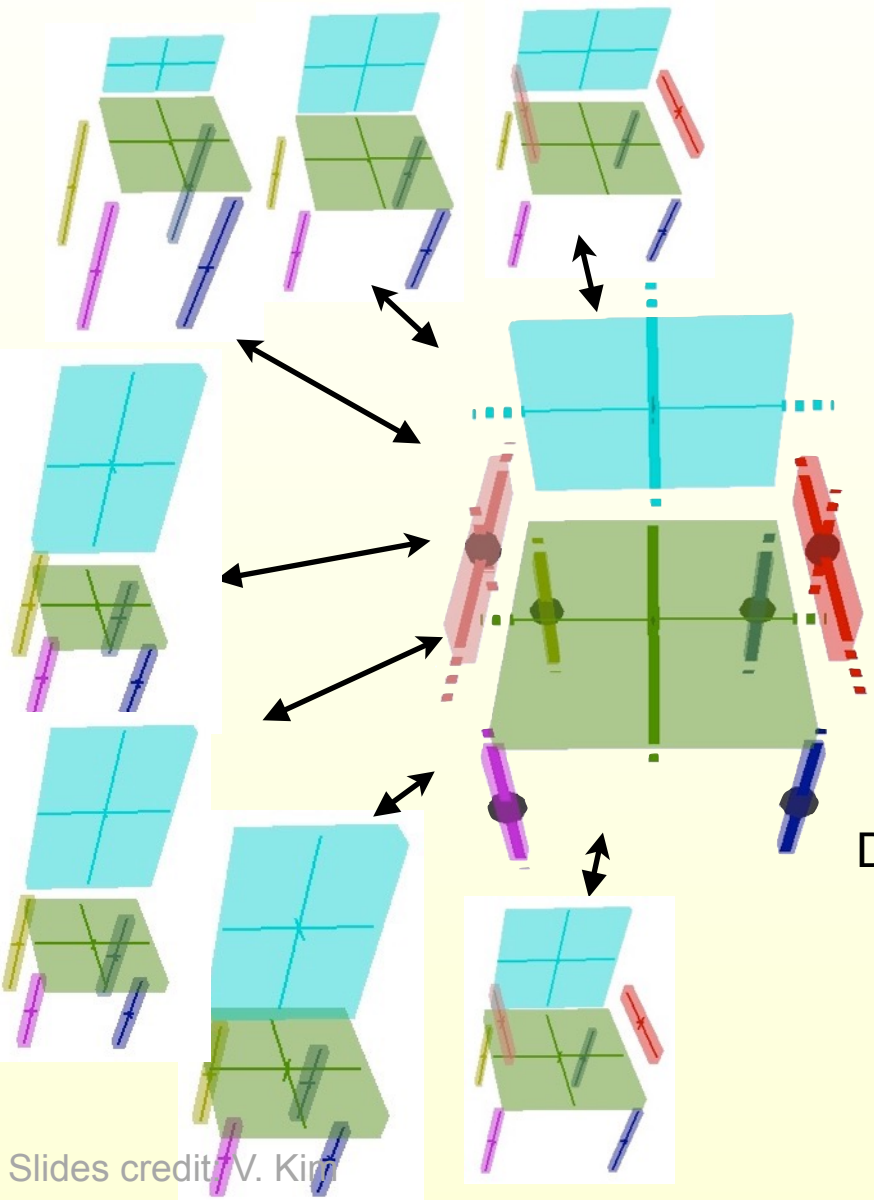
Box-like Templates



Deformable Template

Slides credit: V. Kim

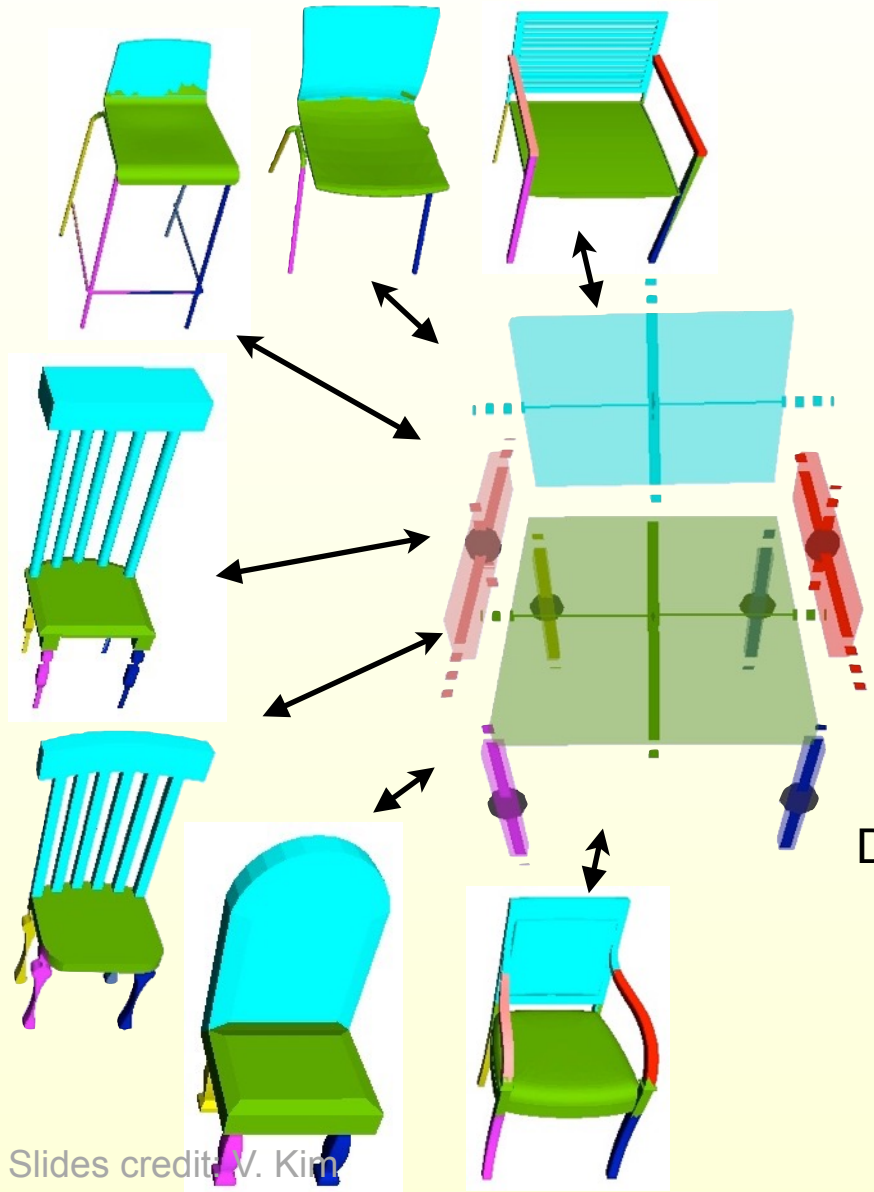
Box-like Templates



Deformable Template

Slides credit: V. Kim

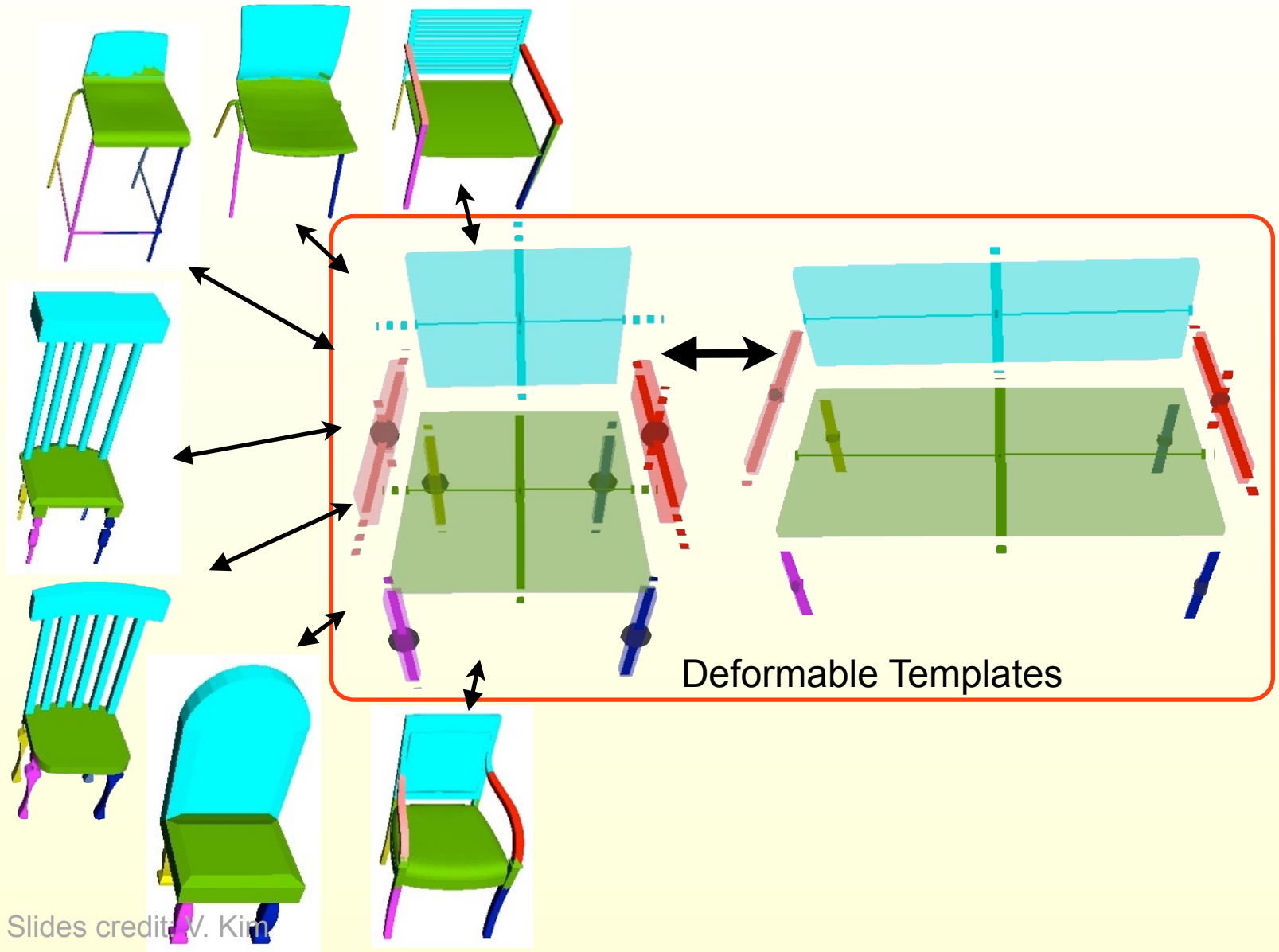
Box-like Templates



Deformable Template

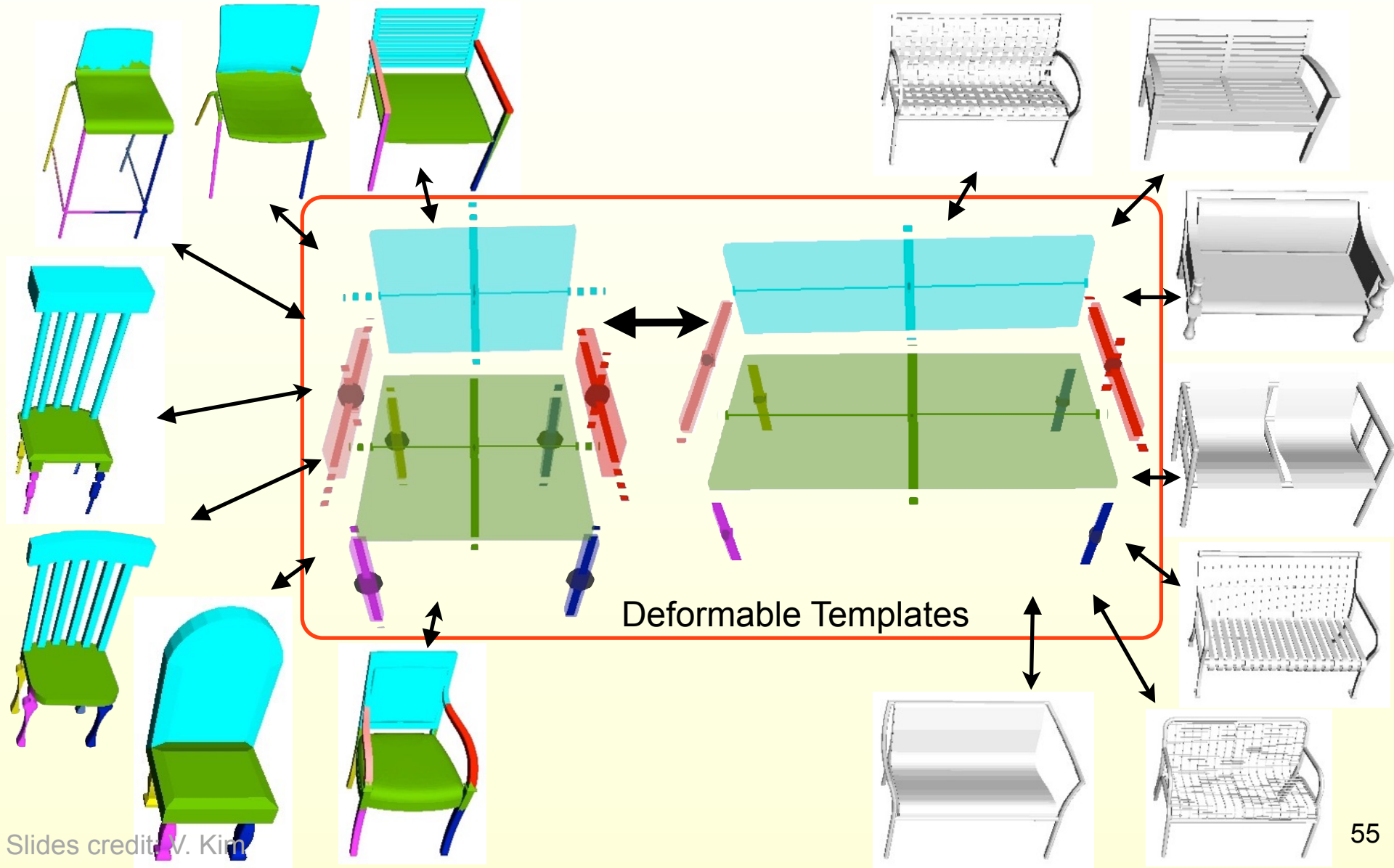
Slides credit: V. Kim

Box-like Templates



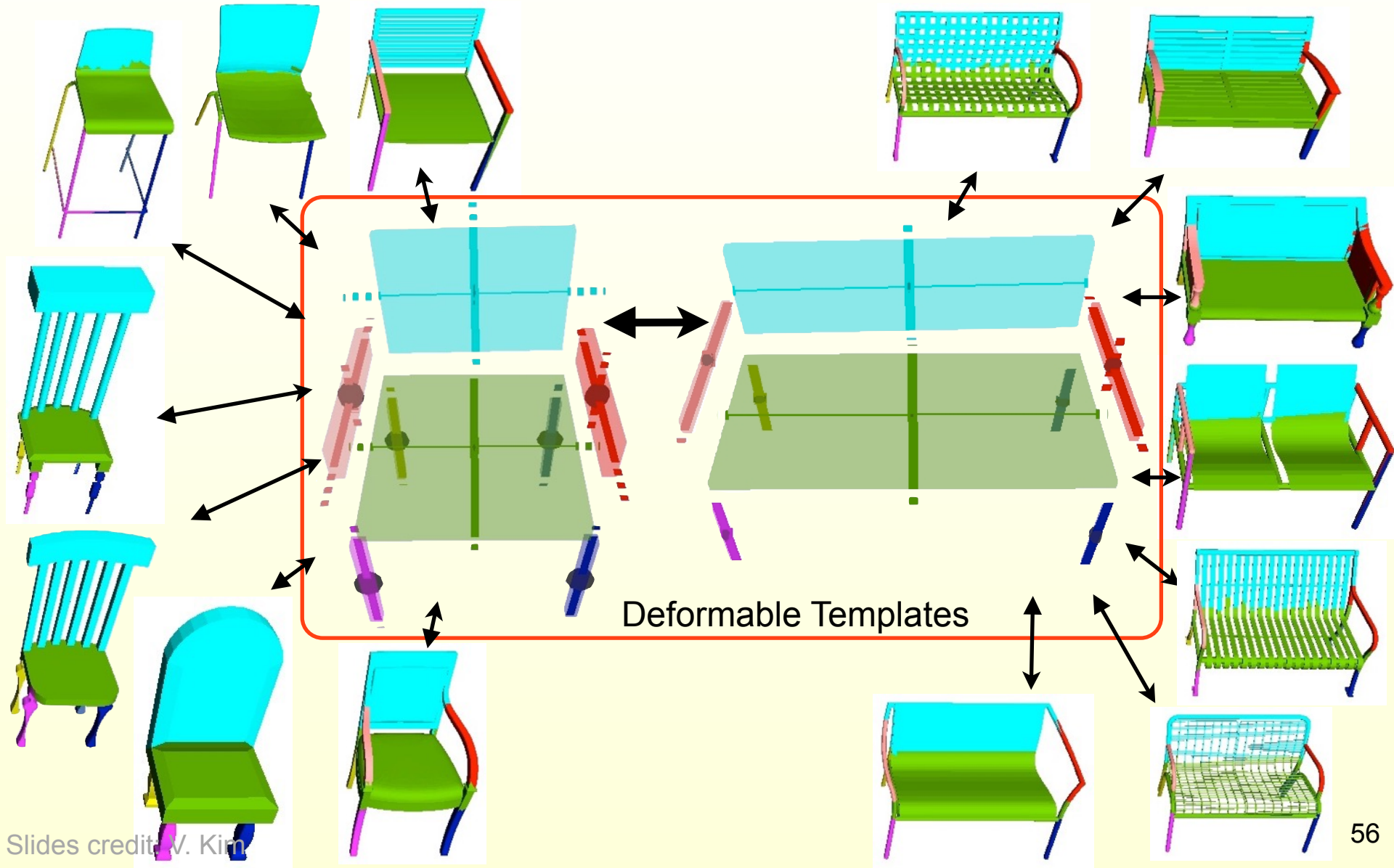
Slides credit: V. Kim

Box-like Templates



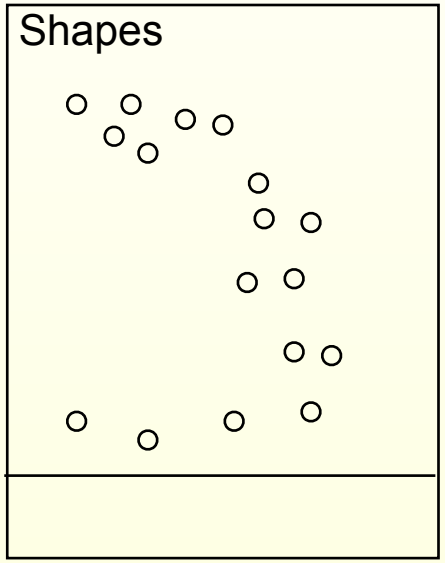
Slides credit: V. Kim

Box-like Templates



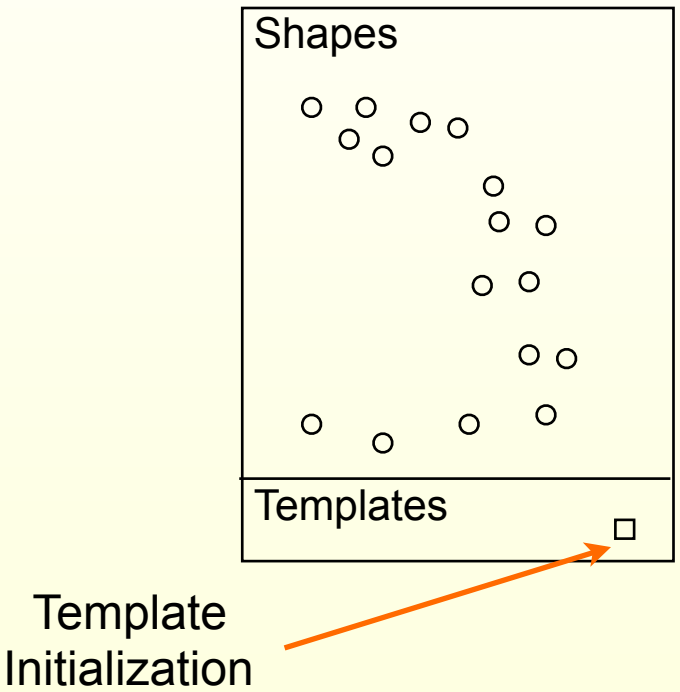
Slides credit: V. Kim

Algorithm Overview

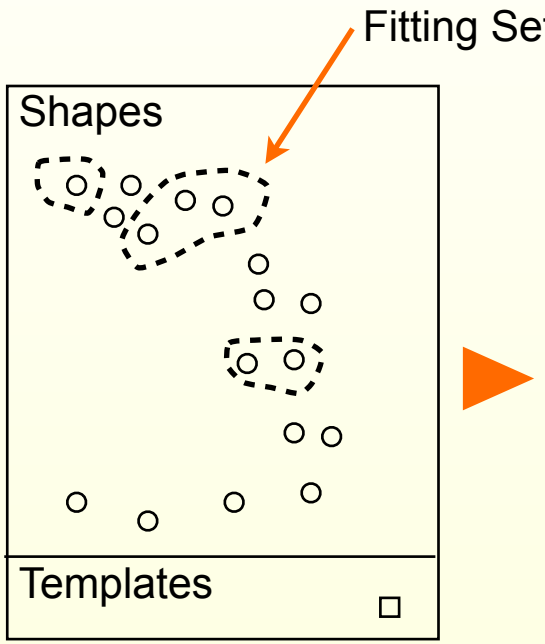


Slides credit: V. Kim

Algorithm Overview



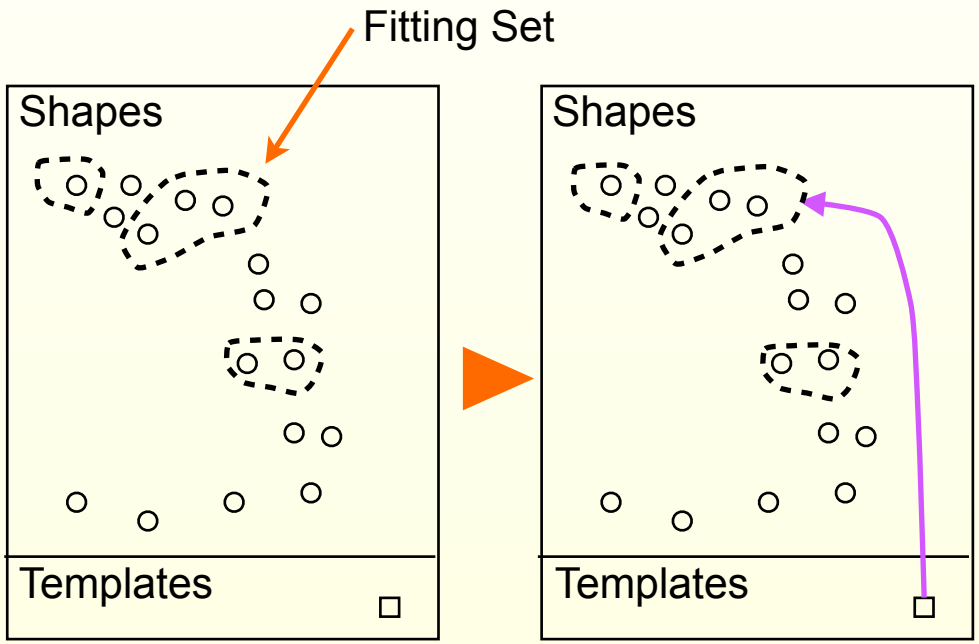
Algorithm Overview



Template Initialization

Template Fitting

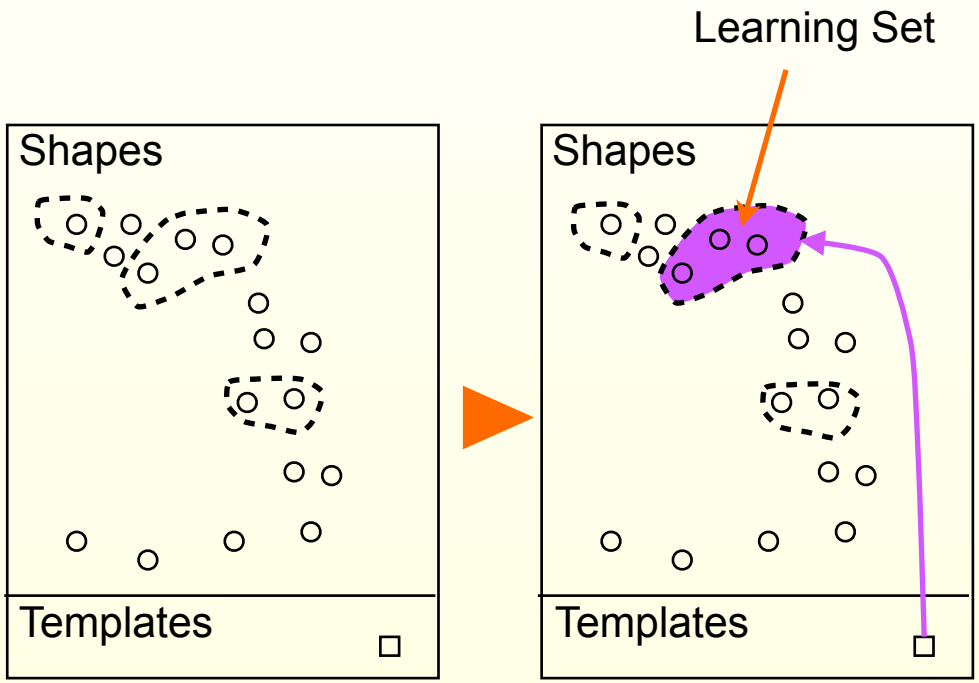
Algorithm Overview



Template Initialization

Template Fitting

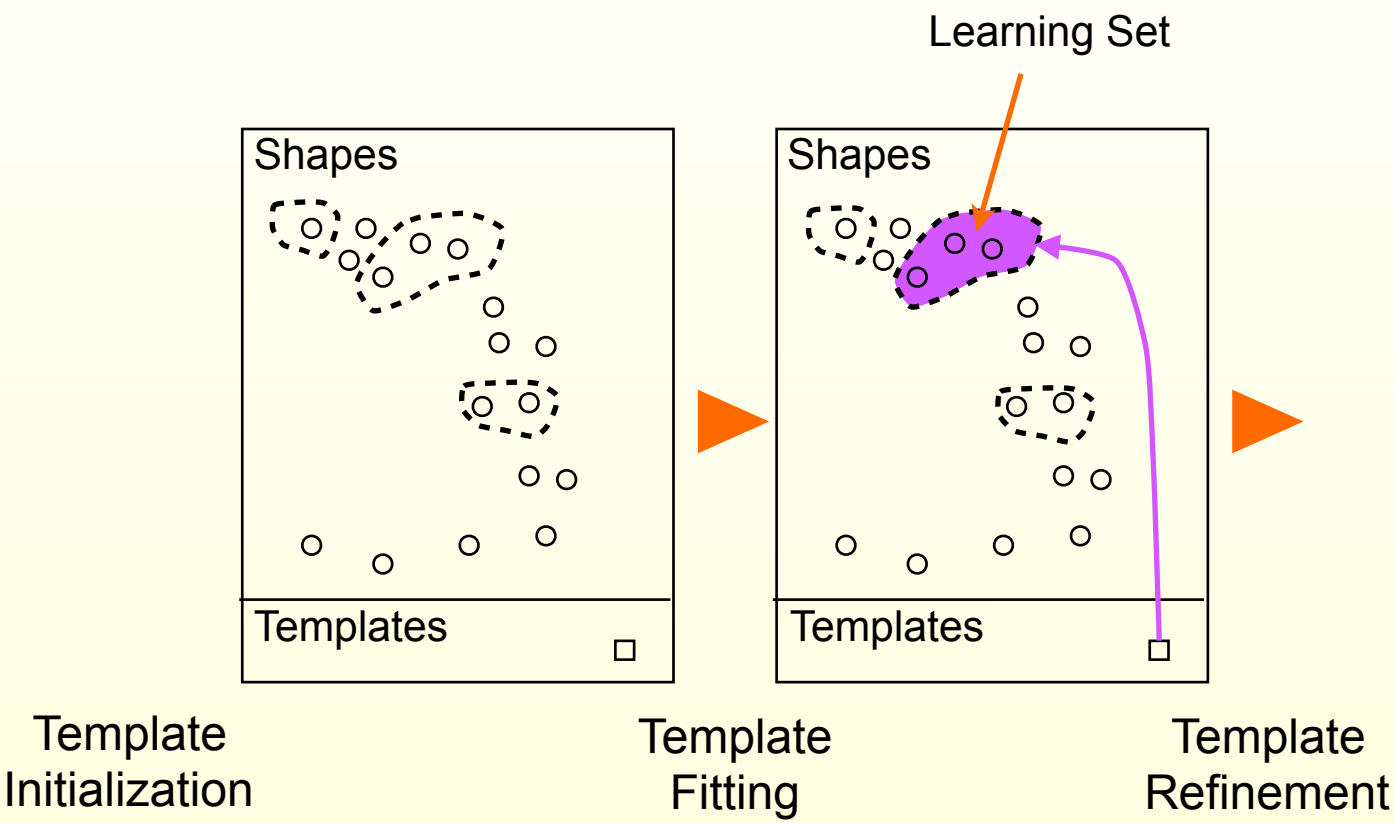
Algorithm Overview



Template Initialization

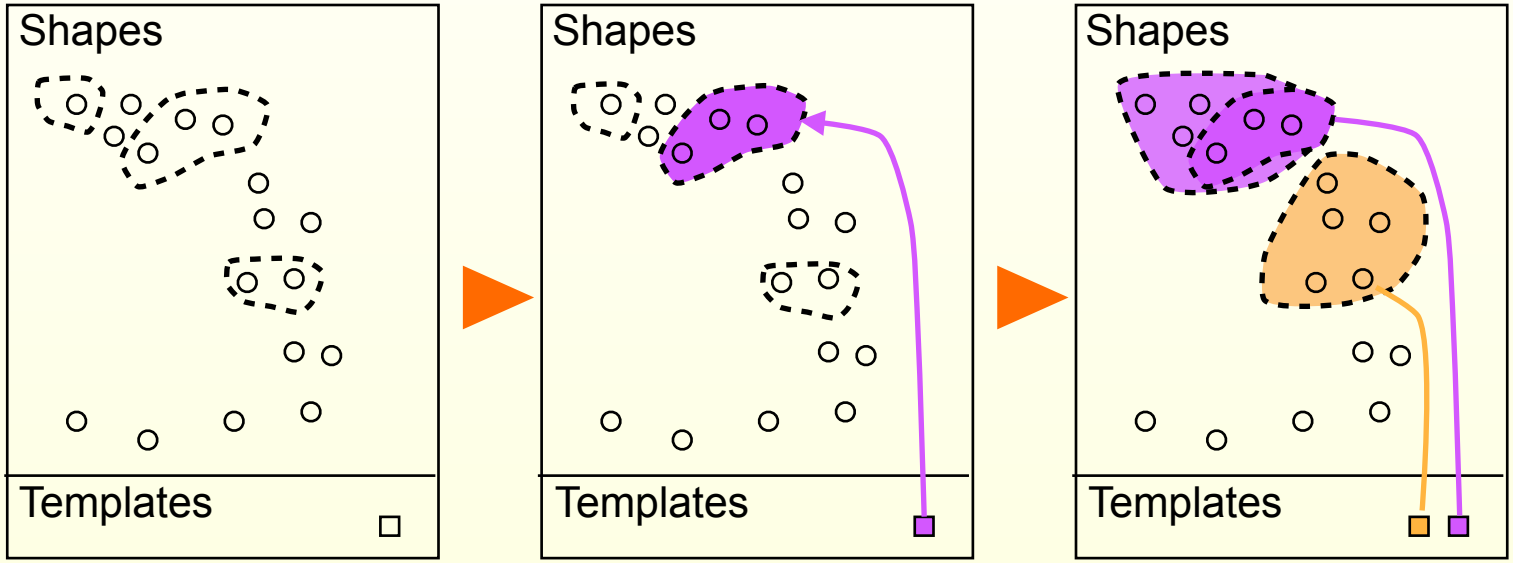
Template Fitting

Algorithm Overview



Slides credit: V. Kim

Algorithm Overview



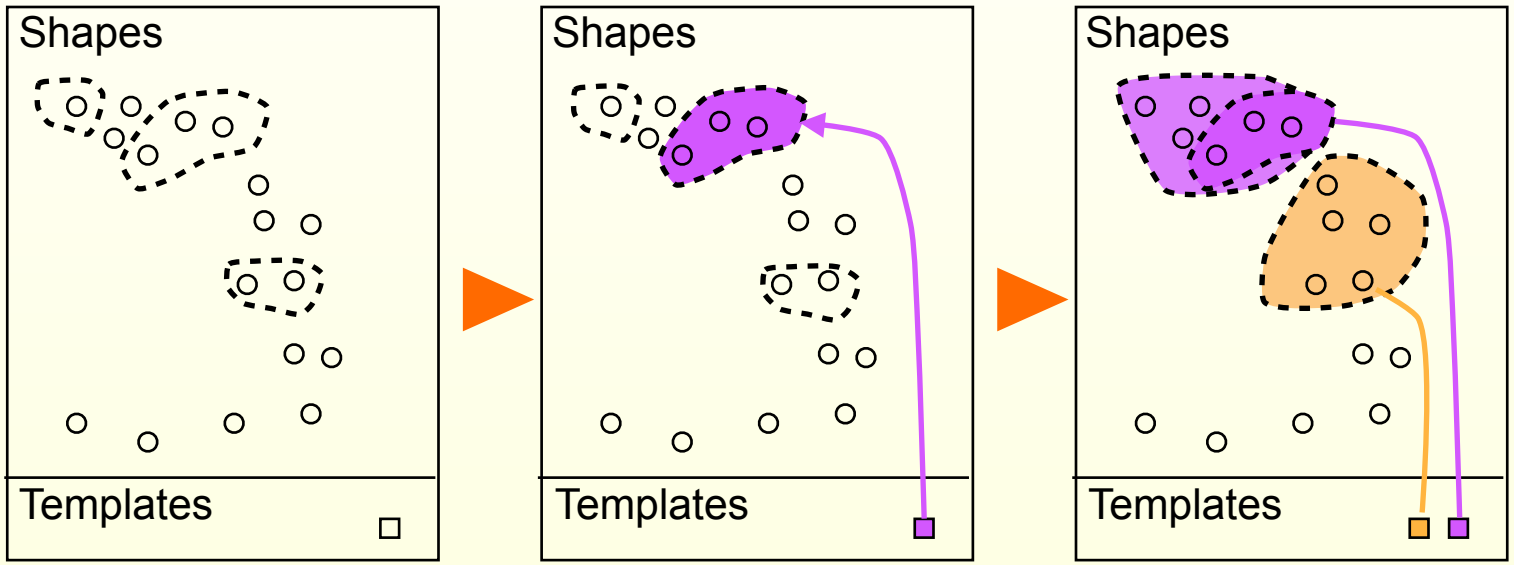
Template Initialization

Template Fitting

Template Refinement

Slides credit: V. Kim

Algorithm Overview



Template Initialization

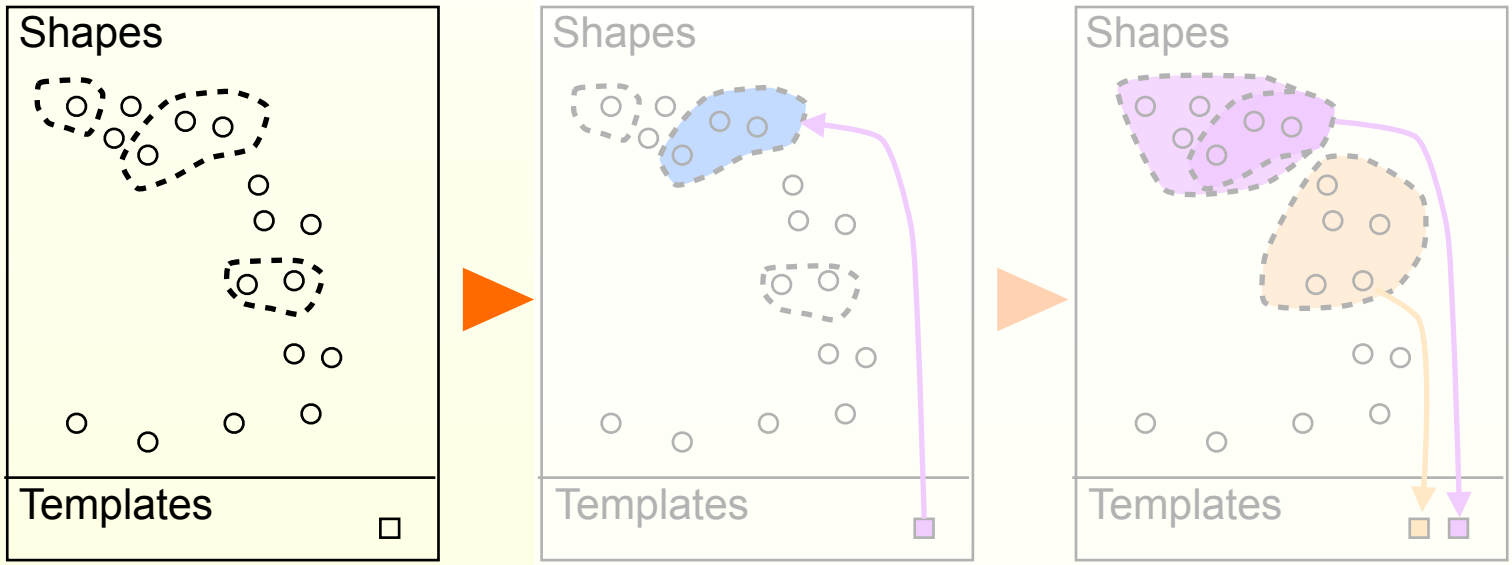
Template Fitting

Template Refinement

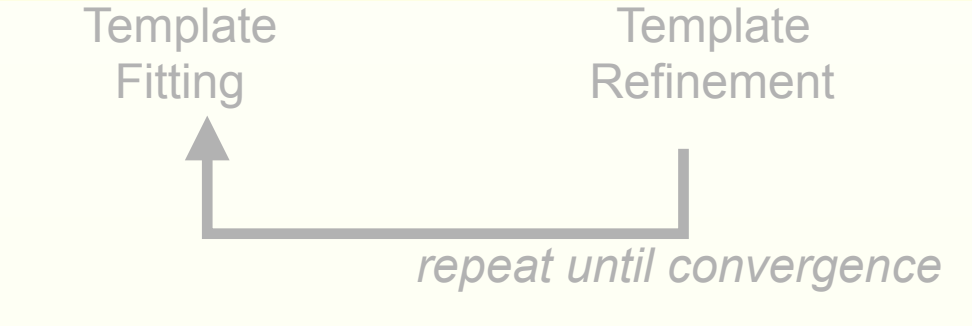
repeat until convergence

Slides credit: V. Kim

Algorithm Overview

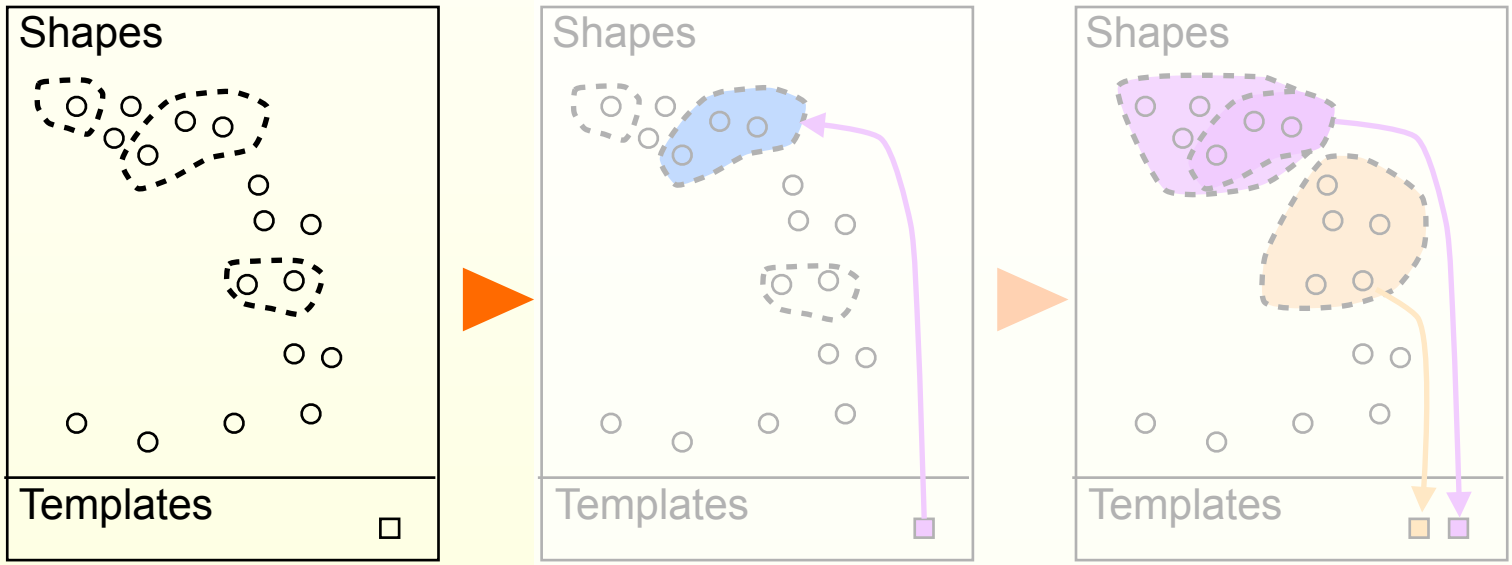


Template Initialization

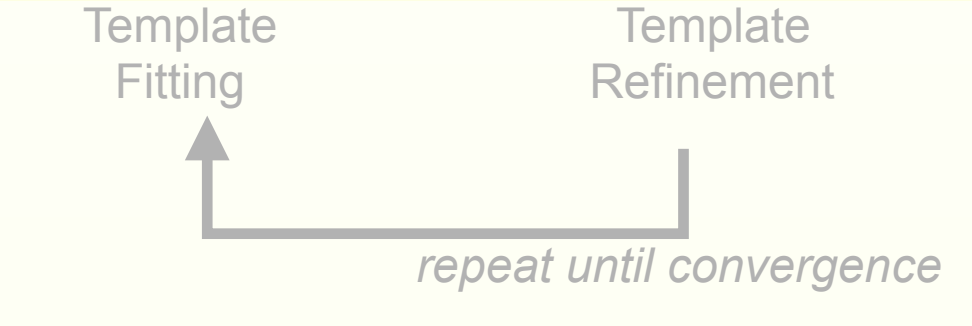


Slides credit: V. Kim

Algorithm Overview



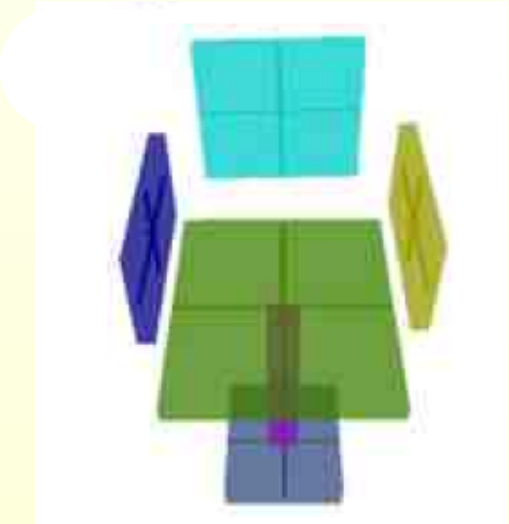
Template Initialization



Slides credit: V. Kim

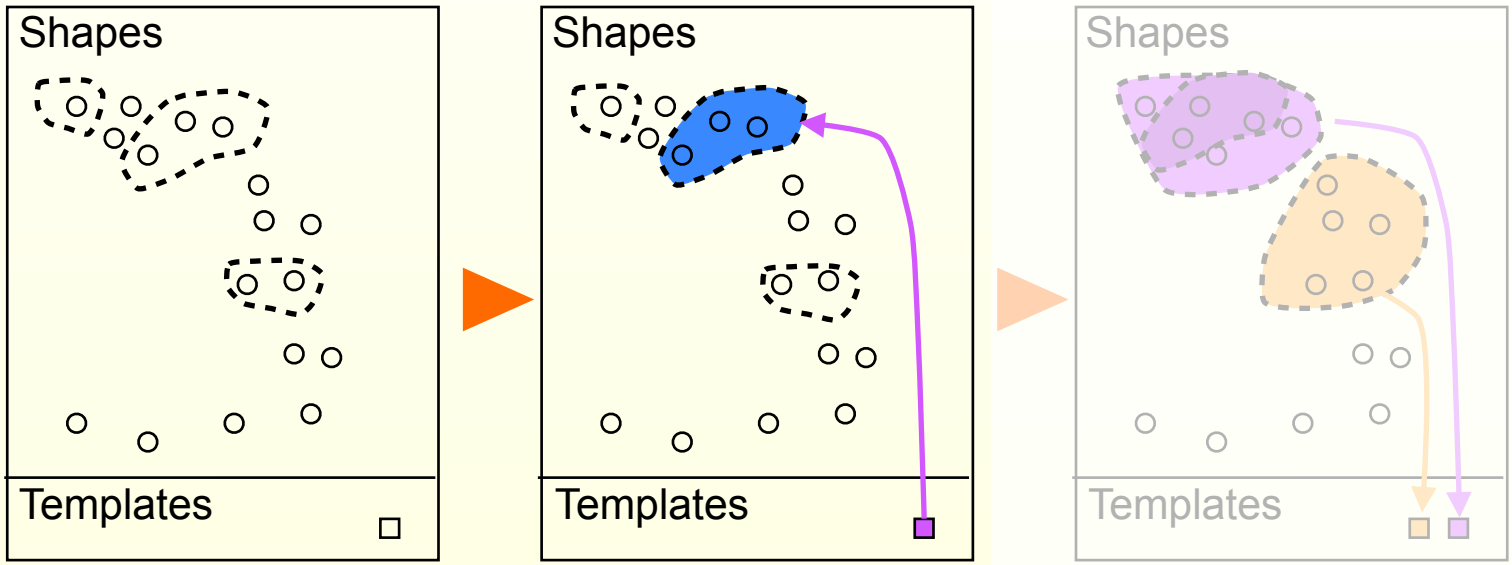
Template Initialization

- Manual initialization
  - The user aligns boxes to semantic parts (≈ 5 min)



Slides credit: V. Kim

Algorithm Overview



Template Initialization

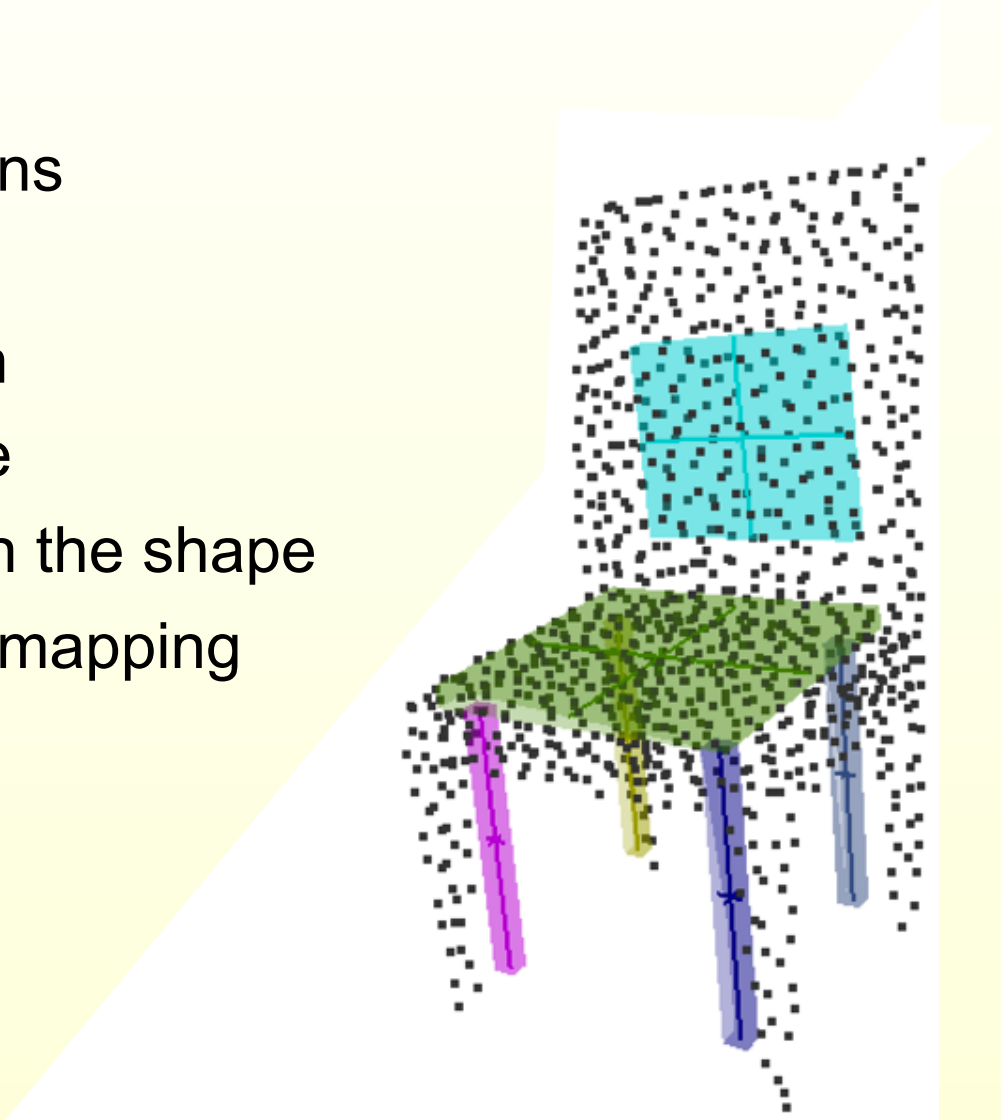
Template Fitting

Template Refinement

Slides credit: V. Kim

Fitting Parameters

- Rigid alignment
- Per part deformations
  - Existence
  - Centroid position
  - Anisotropic scale
- Labeling of points in the shape
- Shape ↔ template mapping



Slides credit: V. Kim

Fitting Energy

$$E = E_{\text{data}} + \gamma E_{\text{deform}} + \beta E_{\text{smooth}}$$

- E_{data} (template $\longleftrightarrow$ shape distance + local shape features)
- E_{deform} (plausibility of template deformation)
- E_{smooth} (close & similar regions should get the same label)

Slides credit: V. Kim

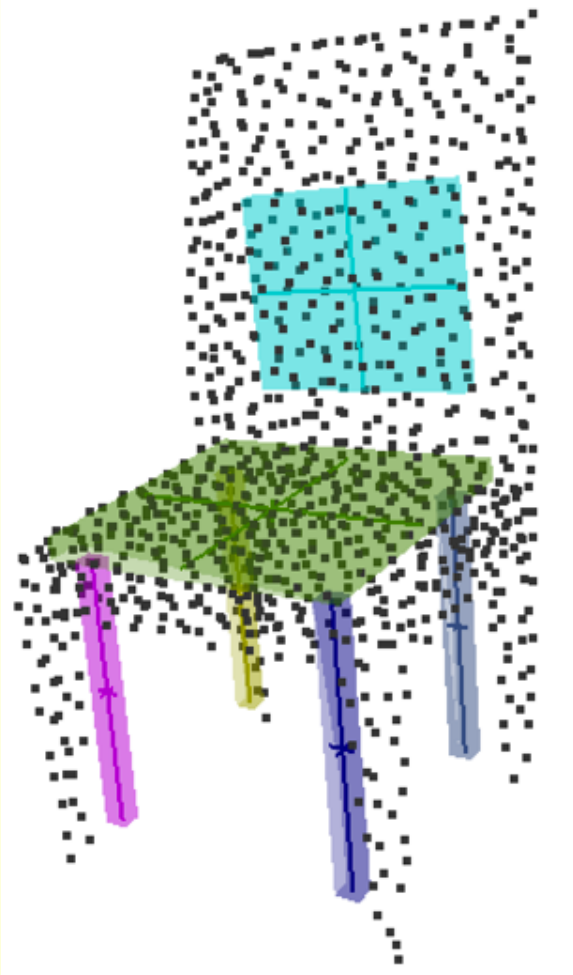
Fitting Optimization

- Alternate steps until shape segmentation converges:
  - Segmentation
  - Correspondences
  - Deformation

Slides credit: V. Kim

Fitting Optimization

- Alternate steps until shape segmentation converges:
  - Segmentation
  - Correspondences
  - Deformation



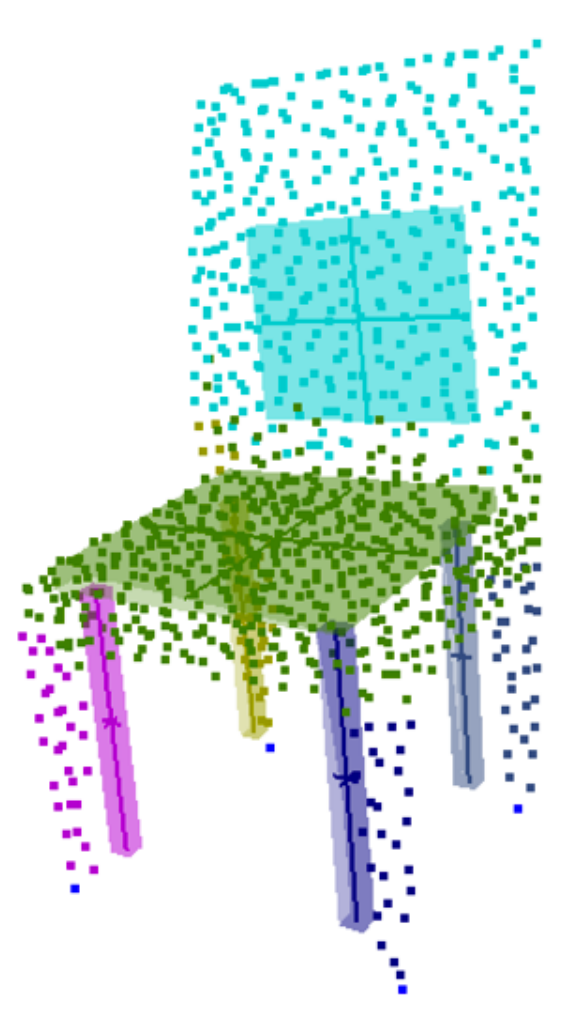
Slides credit: V. Kim

Fitting Optimization

- Alternate steps until shape segmentation converges:
  - Segmentation
  - Correspondences
  - Deformation

$$E = E_{\text{data}} + \gamma E_{\text{deform}} + \beta E_{\text{smooth}}$$

Method: Graph cut [Boykov et al. 2001]



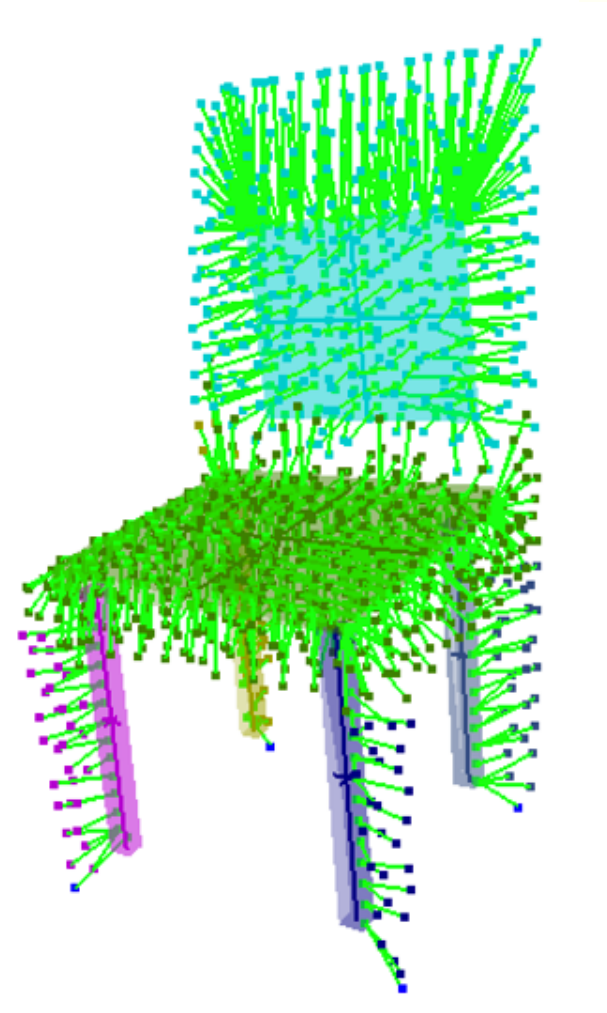
Slides credit: V. Kim

Fitting Optimization

- Alternate steps until shape segmentation converges:
  - Segmentation
    - Correspondences
  - Deformation

$$E = \underline{E_{\text{data}}} + \gamma E_{\text{deform}} + \beta E_{\text{smooth}}$$

Method: Part-aware closest points



Slides credit: V. Kim

Fitting Optimization

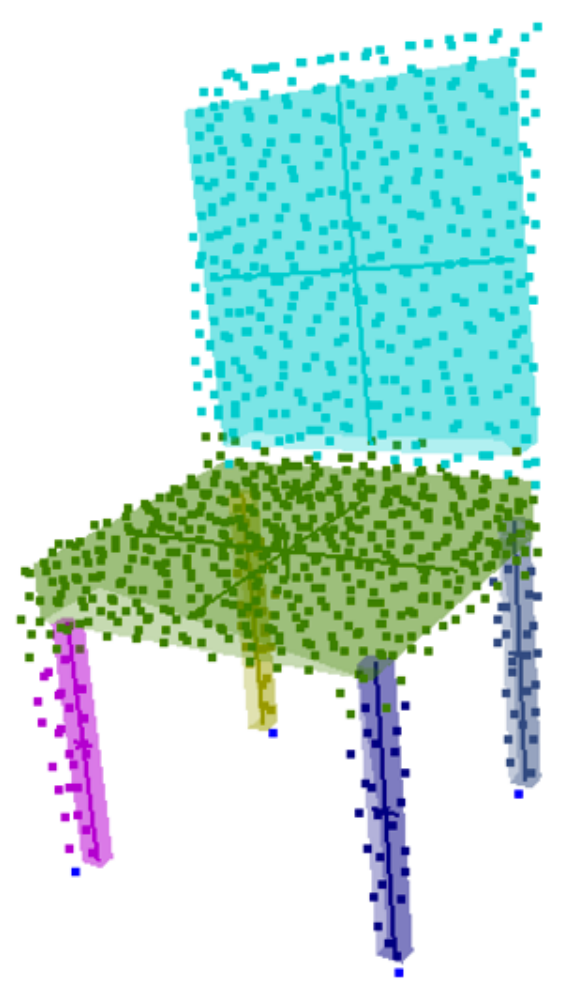
- Alternate steps until shape segmentation converges:
  - Segmentation
  - Correspondences
    - Deformation

$$E = \underline{E_{\text{data}}} + \gamma \underline{E_{\text{deform}}} + \beta E_{\text{smooth}}$$

Method: Solve for critical points.

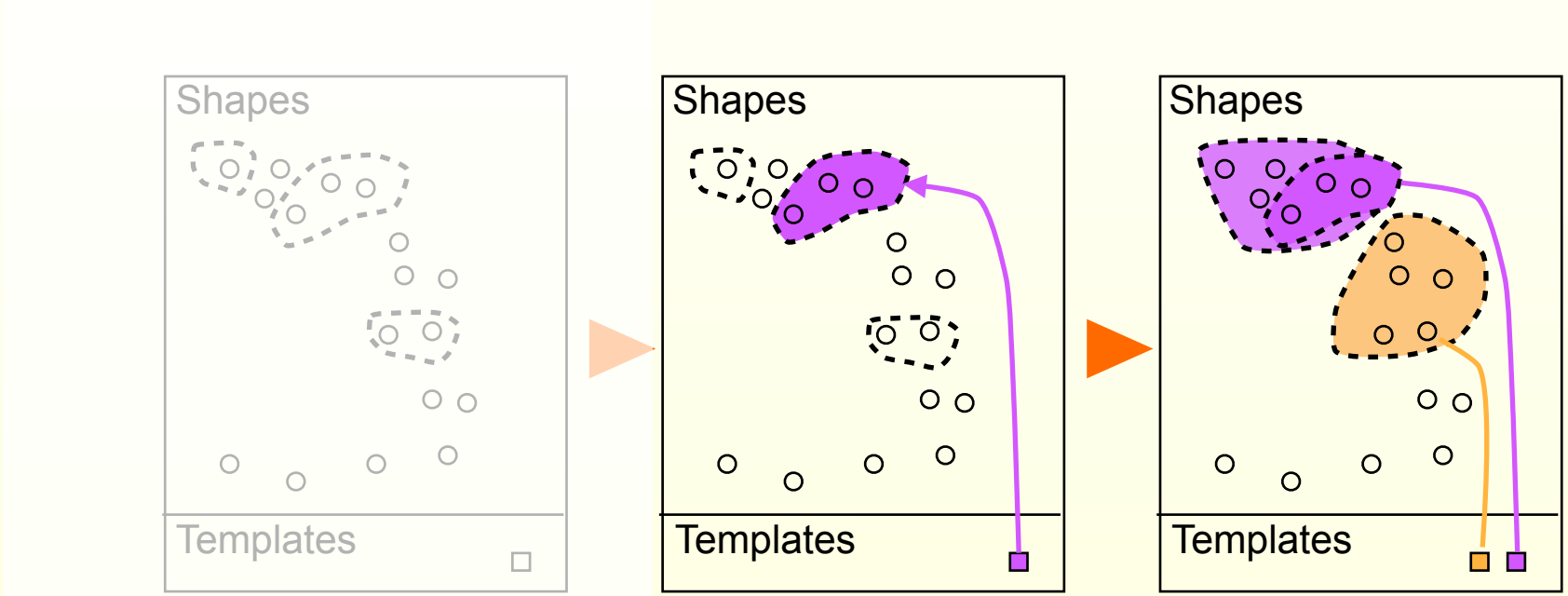
position: $$\frac{\partial(E_{\text{data}} + E_{\text{deform}})}{\partial b_p} = 0$$

scale: $$\frac{\partial(E_{\text{data}} + E_{\text{deform}})}{\partial b_s} = 0$$



Slides credit: V. Kim

Algorithm Overview



Template Initialization

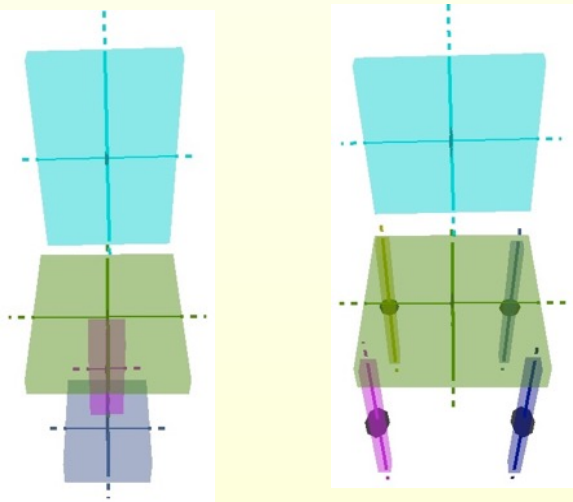
Template Fitting

Template Refinement

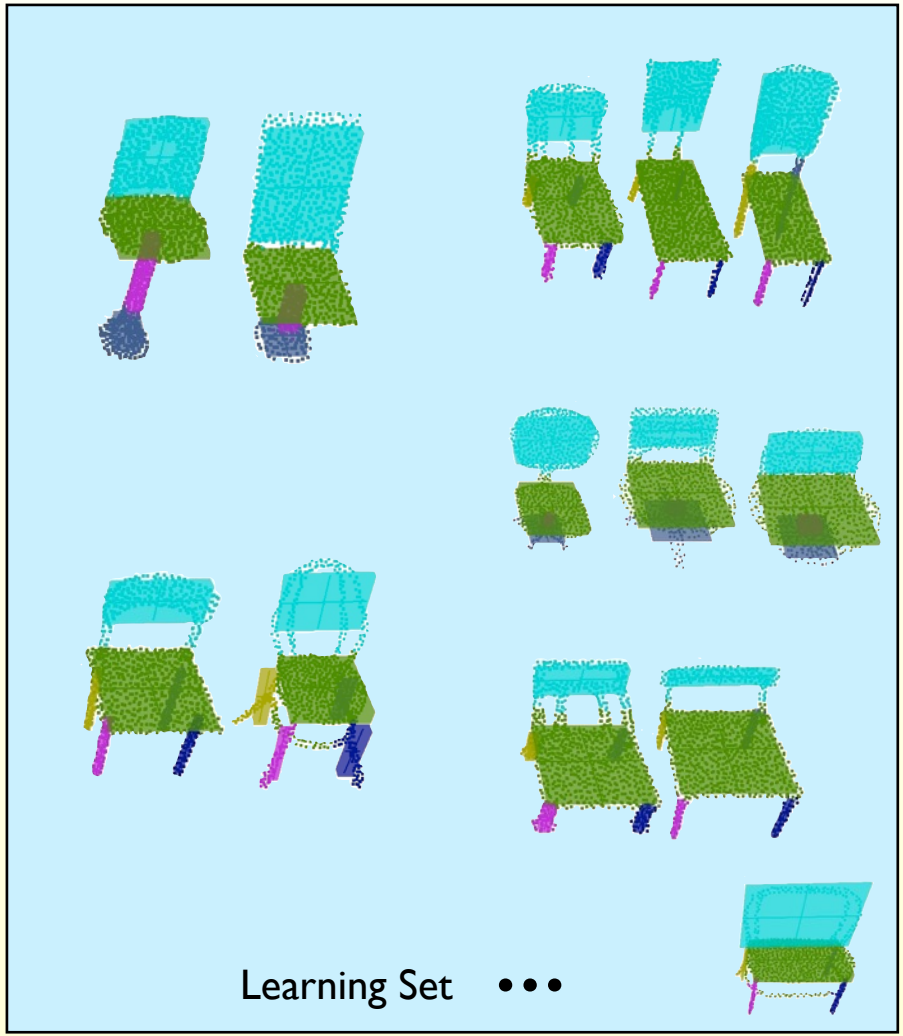
Slides credit: V. Kim

Template Refinement

- Update template set from deformations in Learning Set
  - Update current
  - Spawn new
  - Reject outliers



Current Template Set

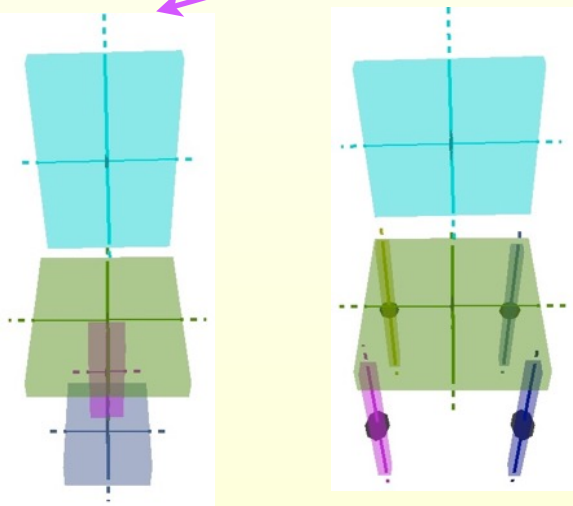


Learning Set •••

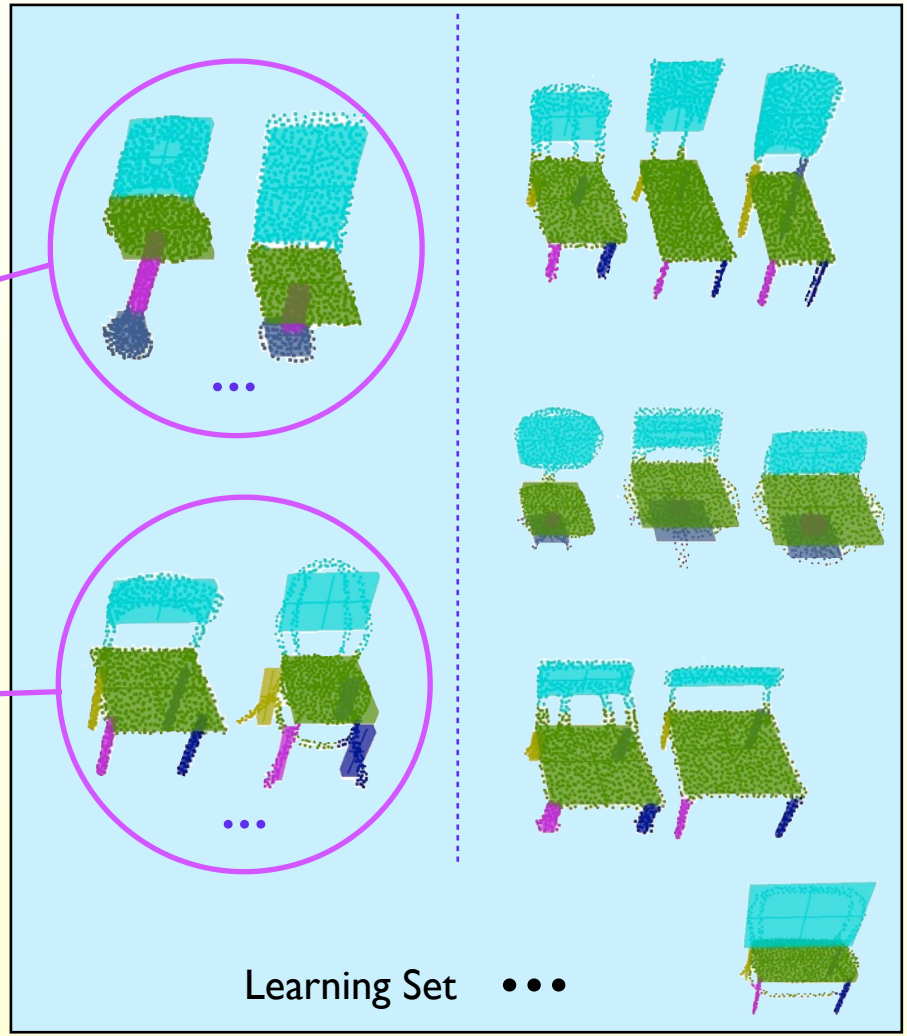
Slides credit: V. Kim

Template Refinement

- Update template set from deformations in Learning Set
  - Update current
  - Spawn new
  - Reject outliers



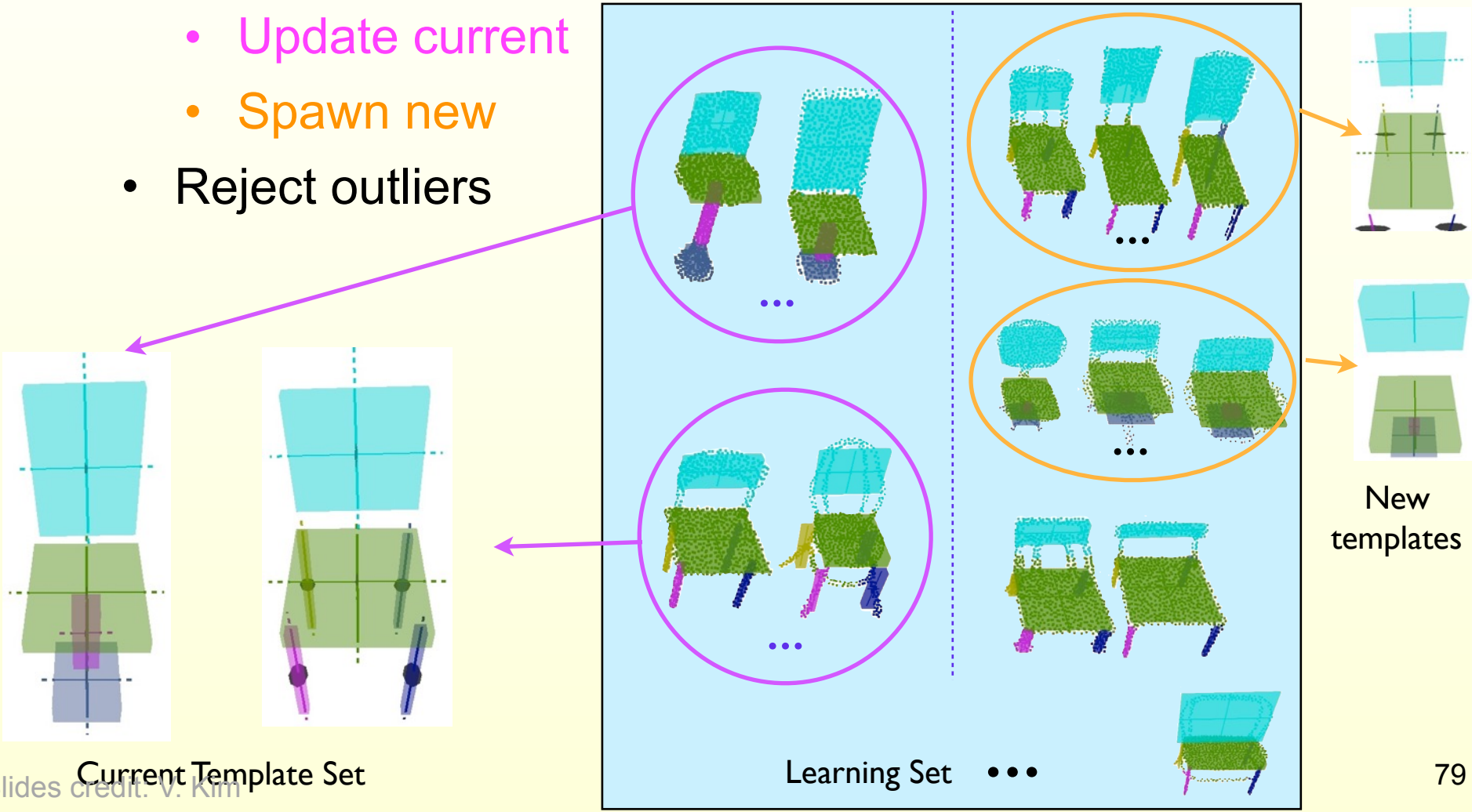
Current Template Set



Learning Set • • •

Template Refinement

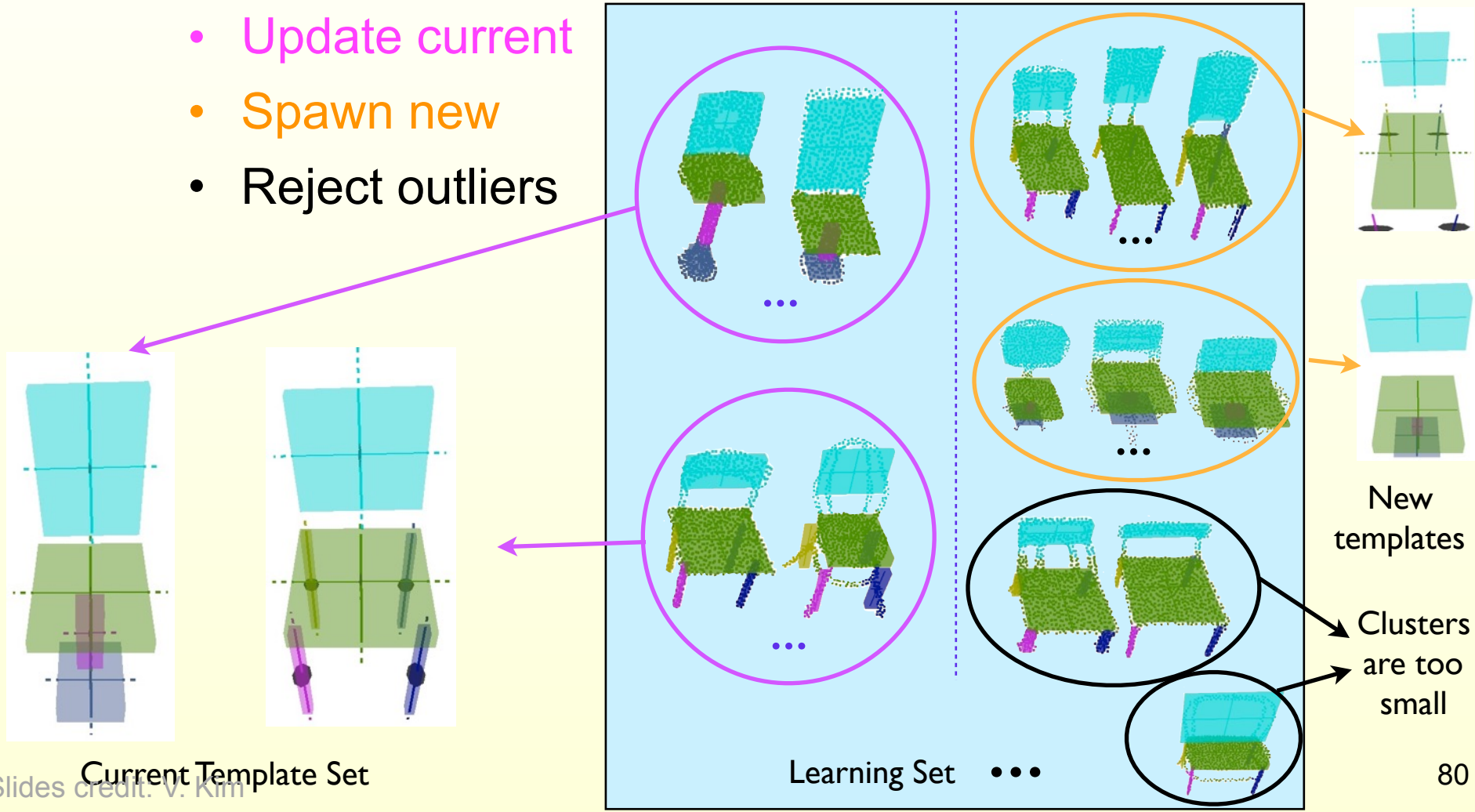
- Update template set from deformations in Learning Set
  - Update current
  - Spawn new
  - Reject outliers



Slides credit: V. Kim

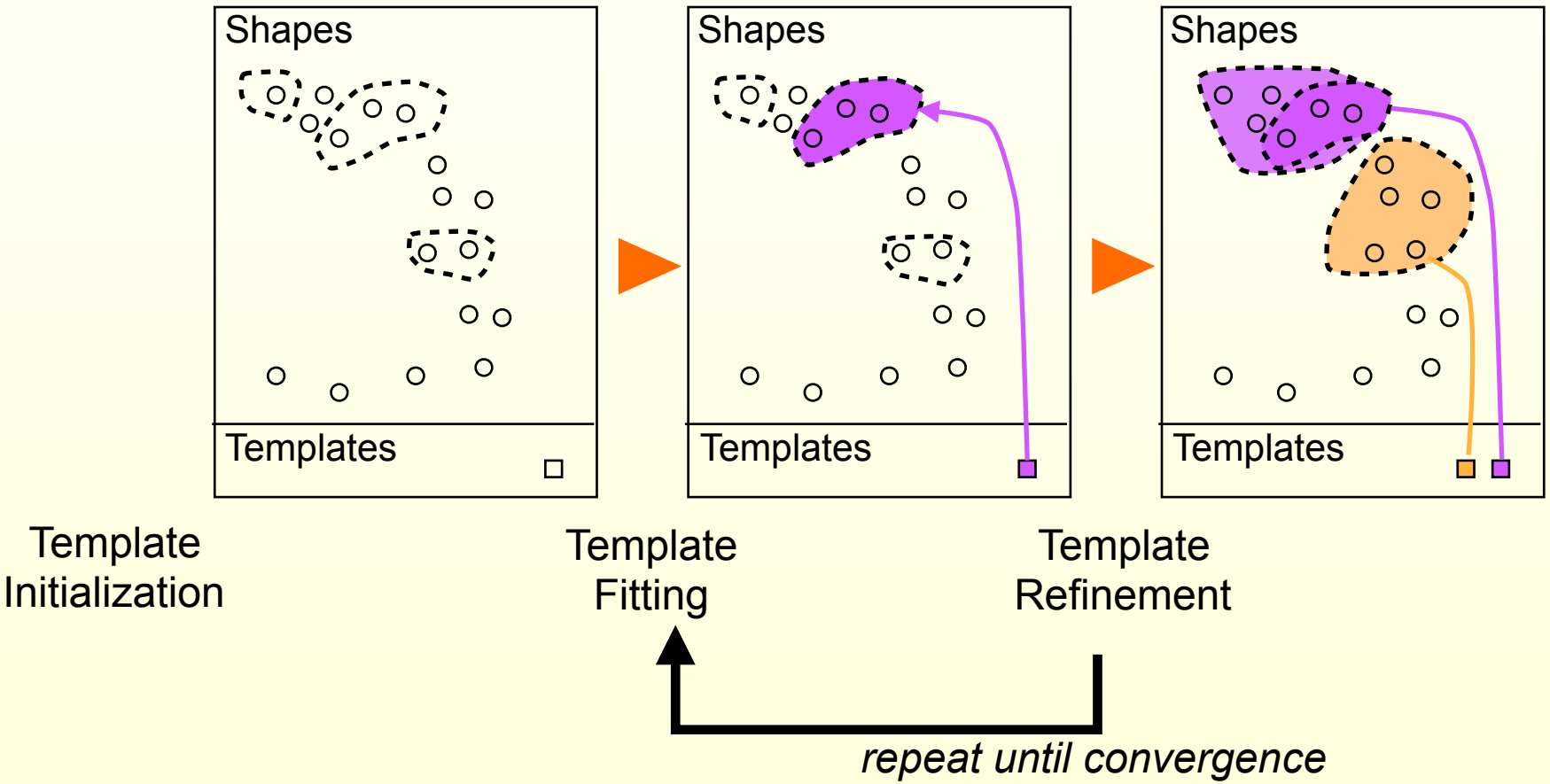
Template Refinement

- Update template set from deformations in Learning Set
  - Update current
  - Spawn new
  - Reject outliers



Slides credit: V. Kim

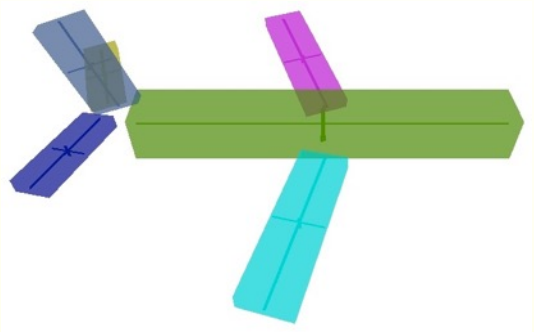
Algorithm Overview



Slides credit: V. Kim

3D Warehouse: 3113 airplanes

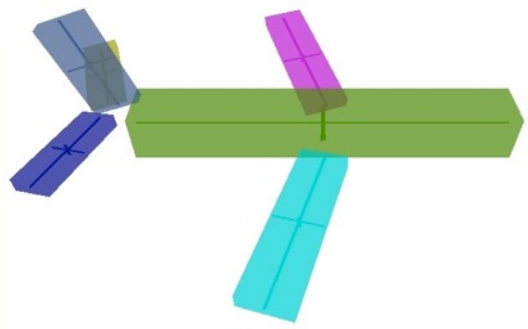
Initial Template:



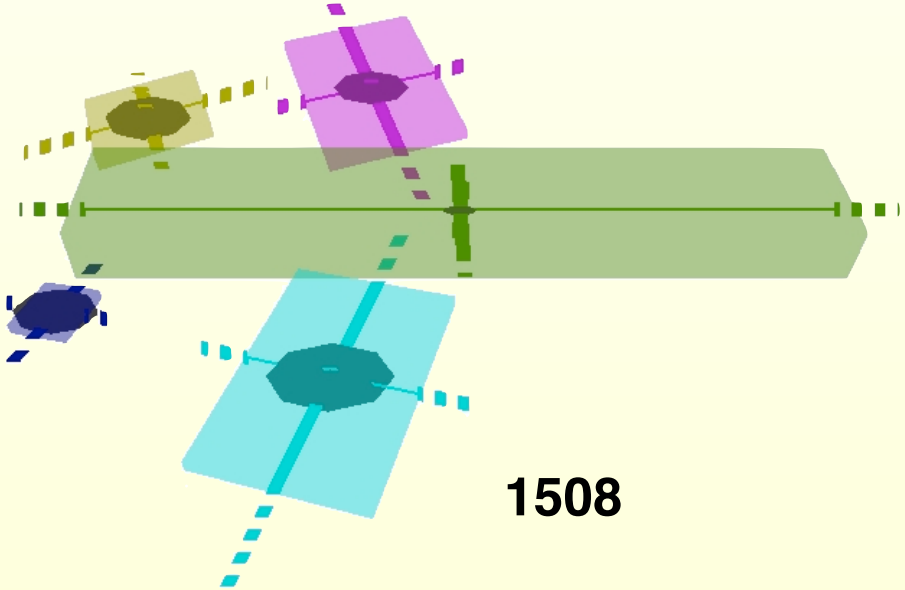
Slides credit: V. Kim

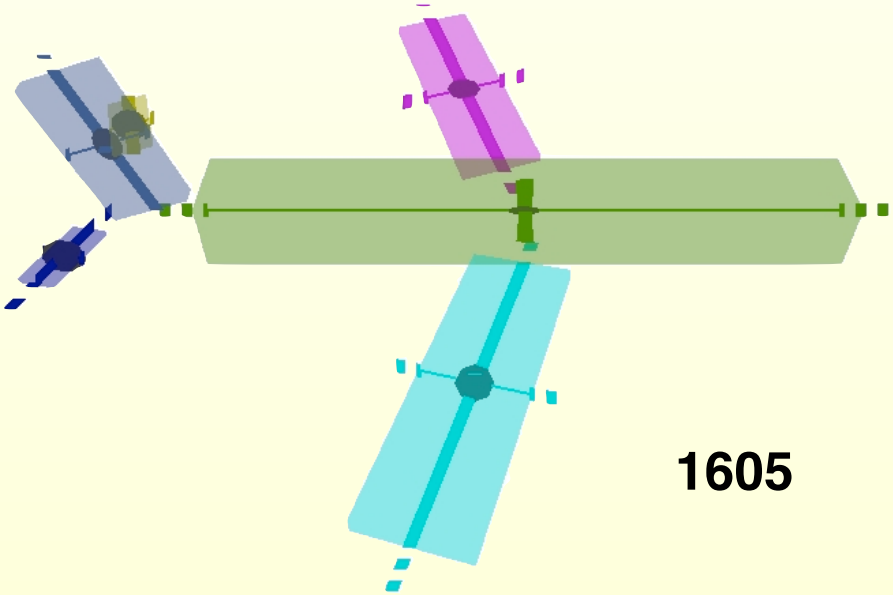
3D Warehouse: 3113 airplanes

Initial Template:



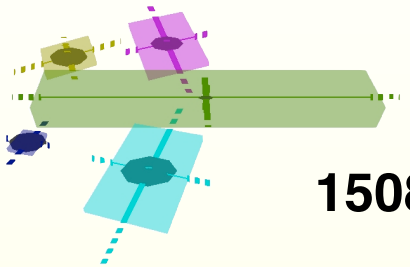
Final Templates:



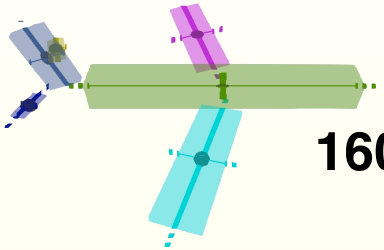


Slides credit: V. Kim

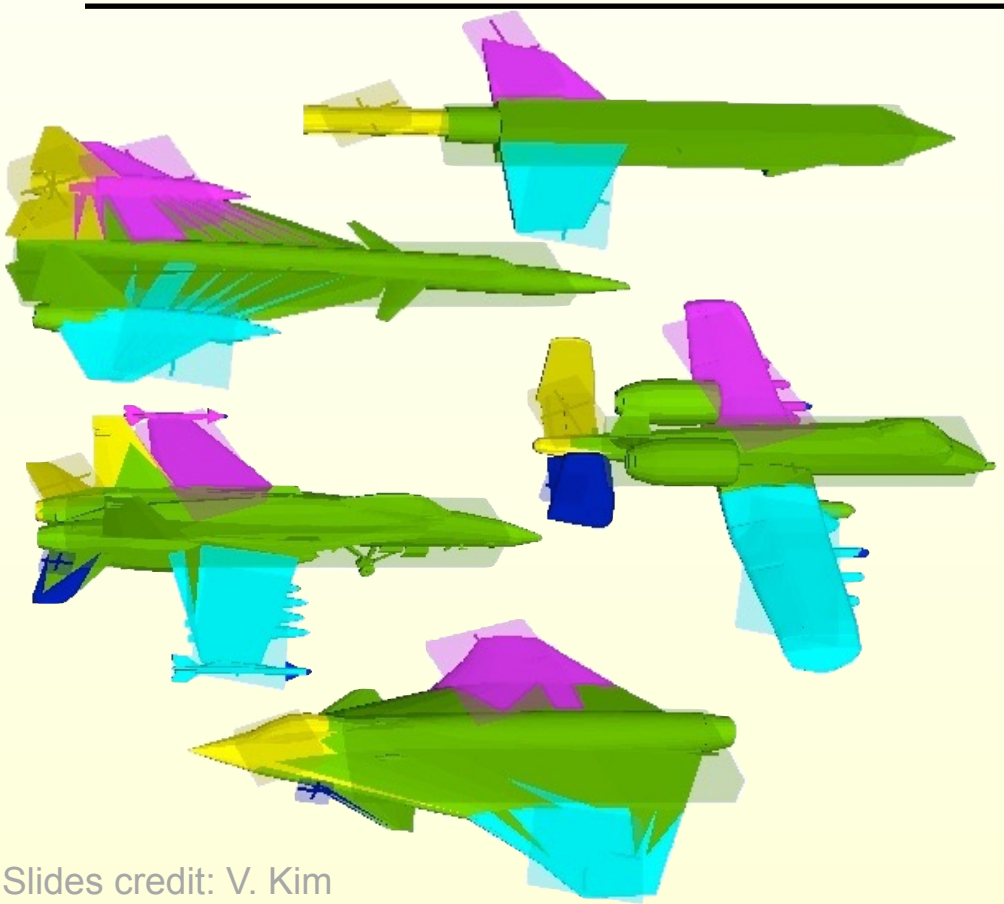
3D Warehouse: 3113 airplanes

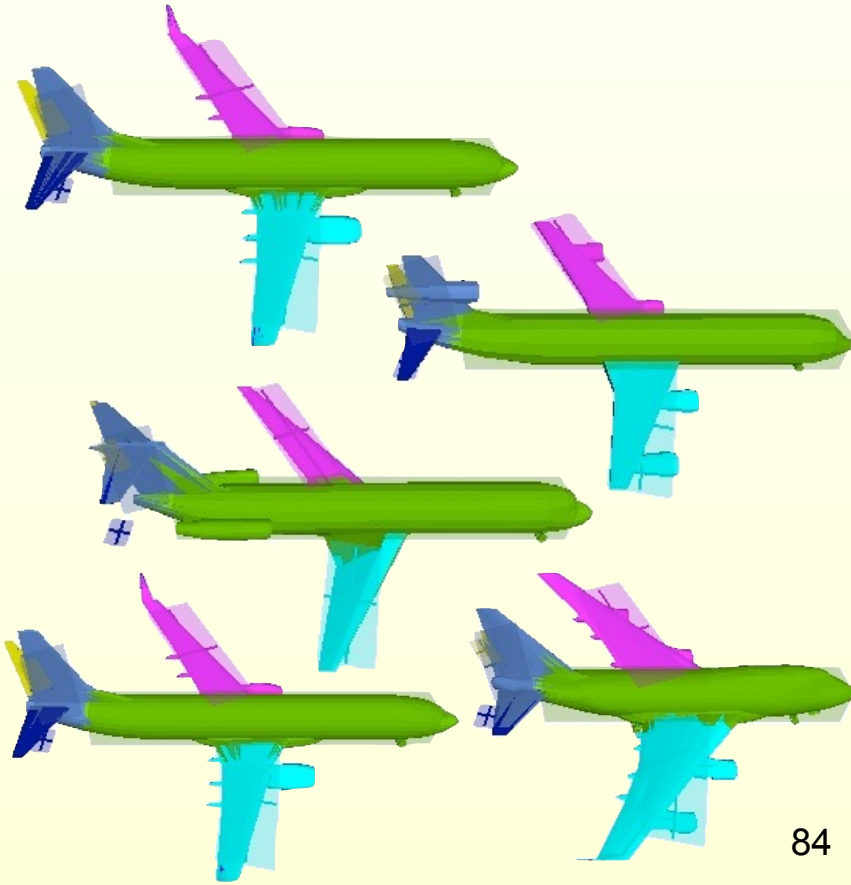


1508



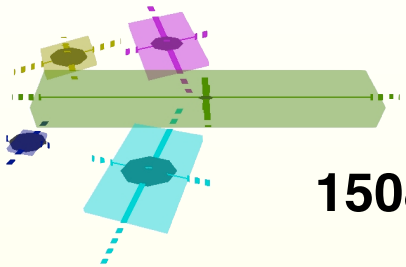
1605



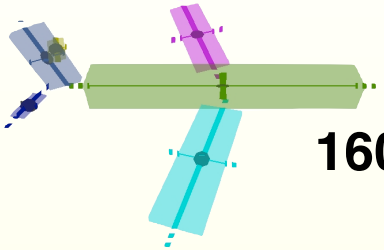


Slides credit: V. Kim

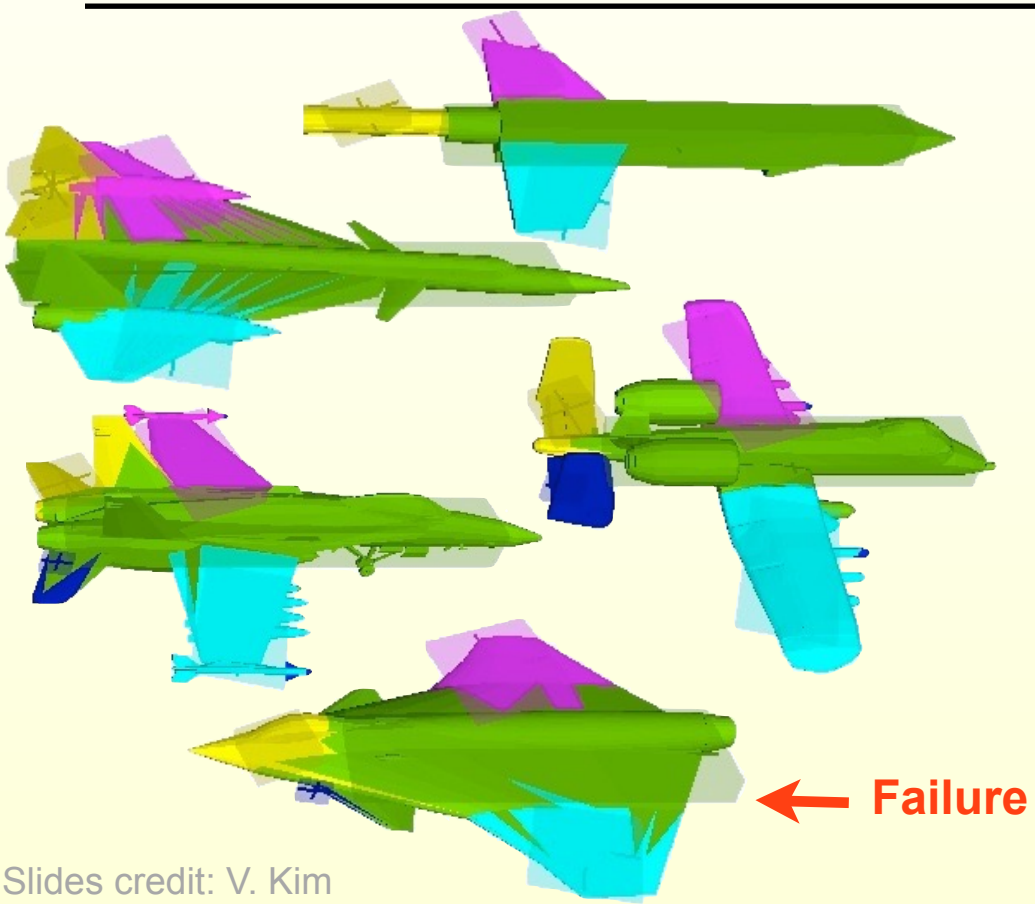
3D Warehouse: 3113 airplanes



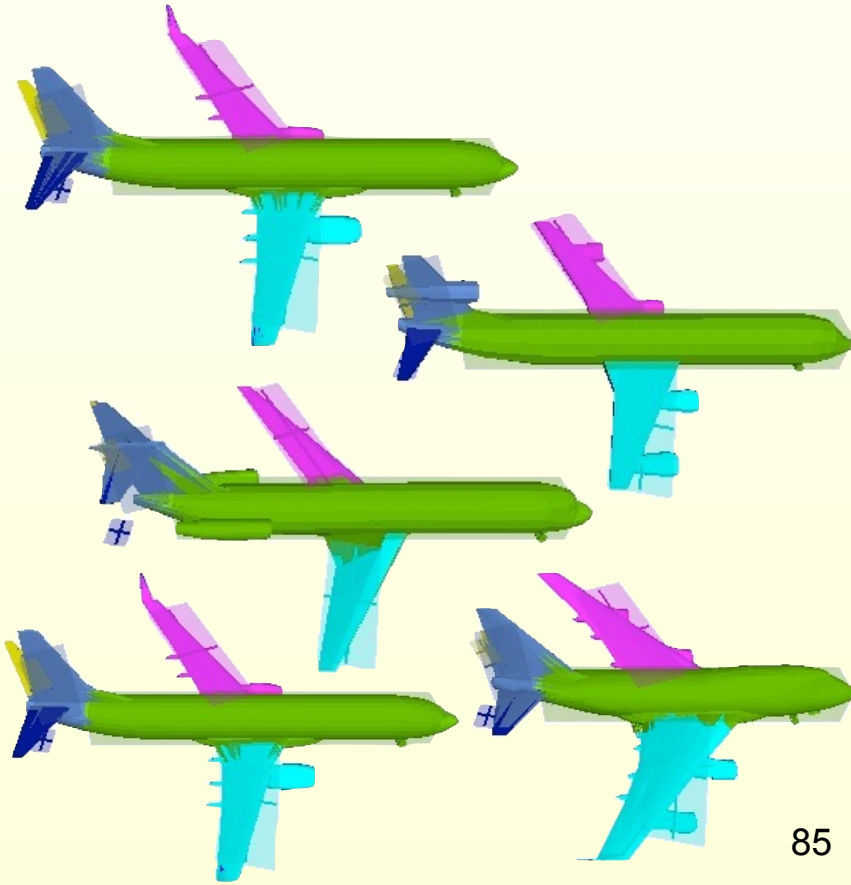
1508



1605



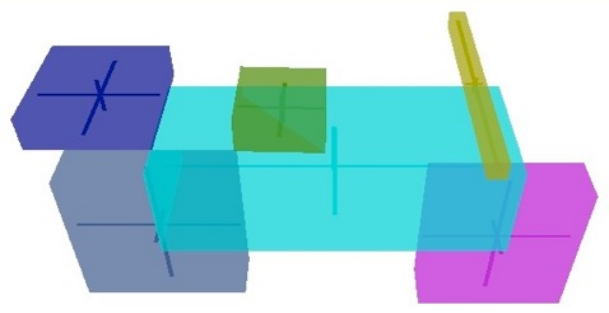
Failure



Slides credit: V. Kim

3D Warehouse: 471 bikes

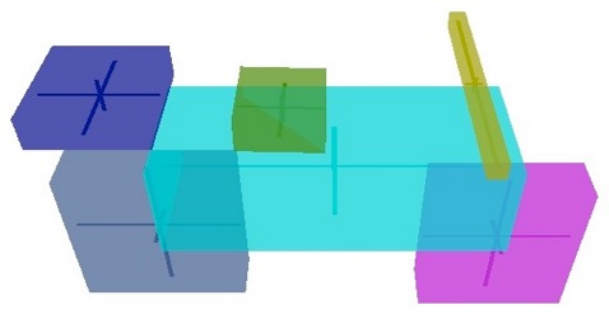
Initial Template:



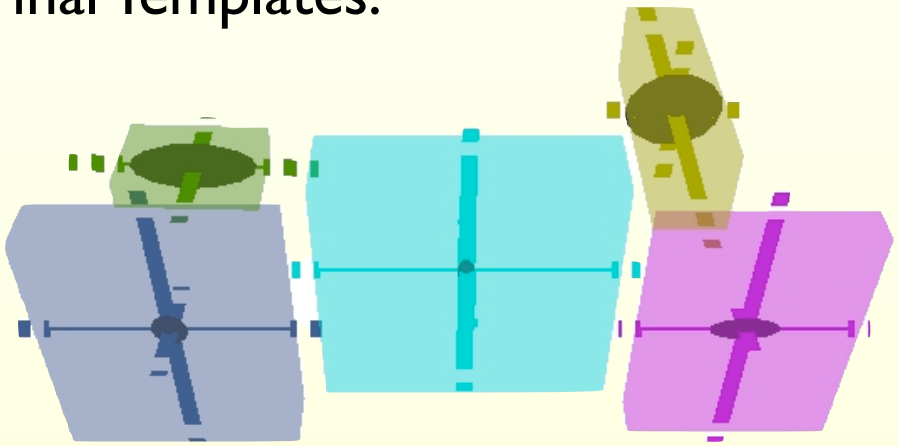
Slides credit: V. Kim

3D Warehouse: 471 bikes

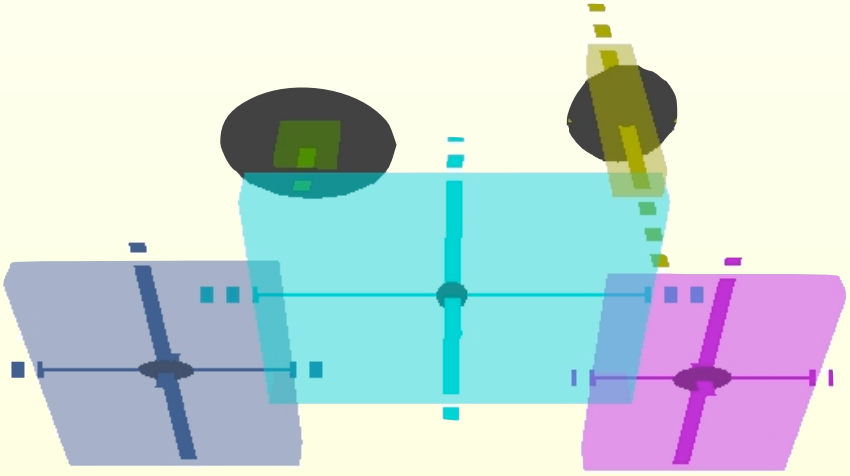
Initial Template:



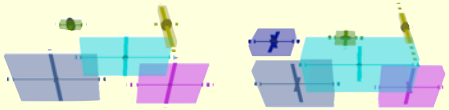
Final Templates:



378



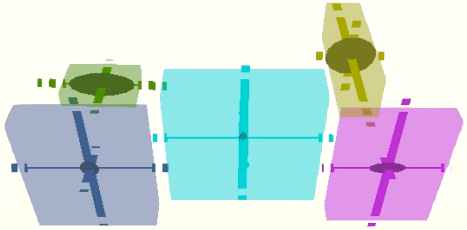
63



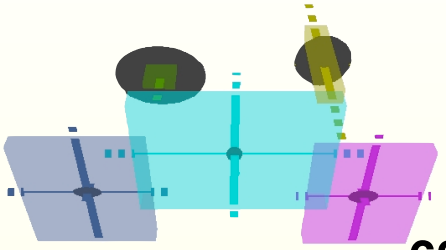
23 7

Slides credit: V. Kim

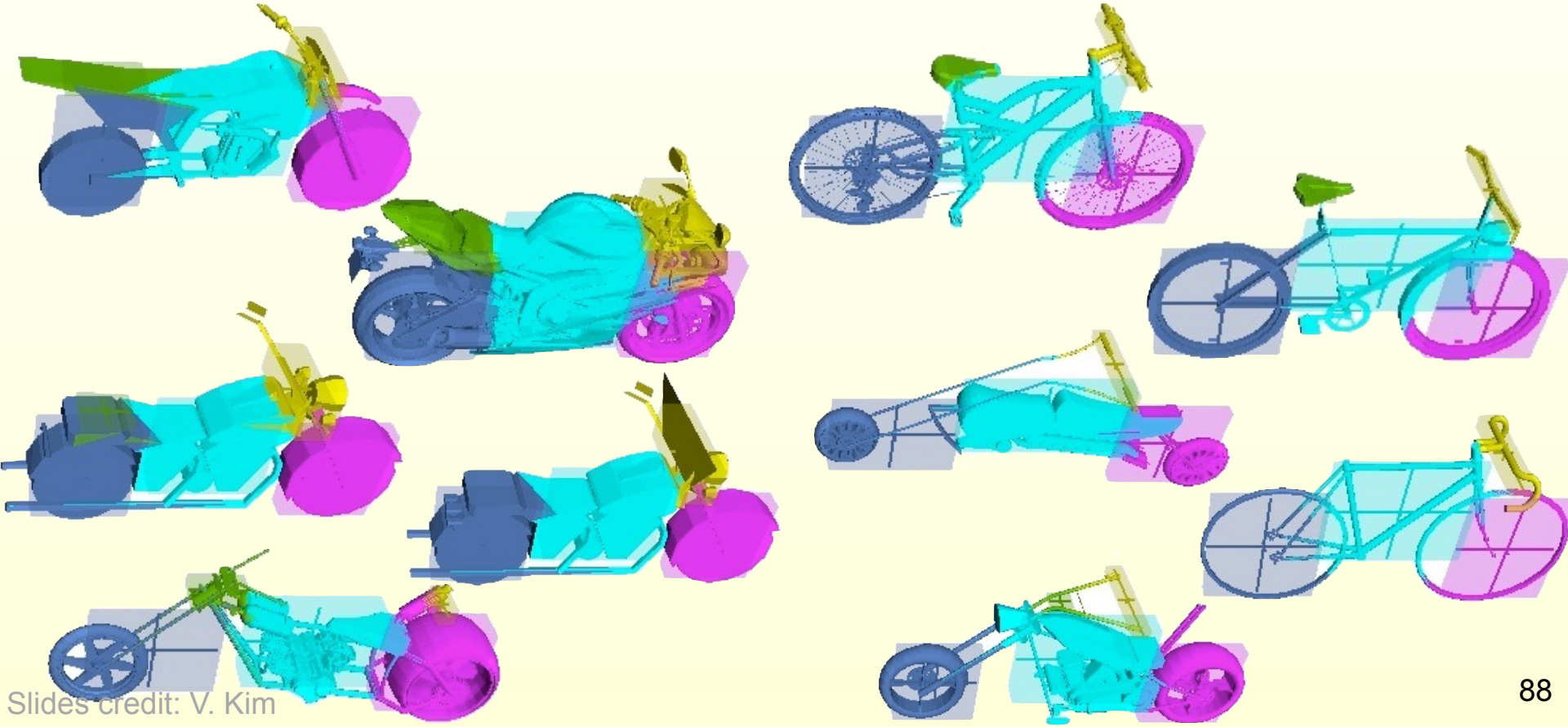
3D Warehouse: 471 bikes



378

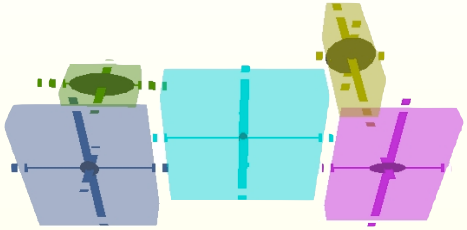


63

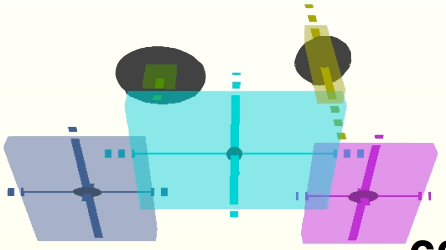


Slides credit: V. Kim

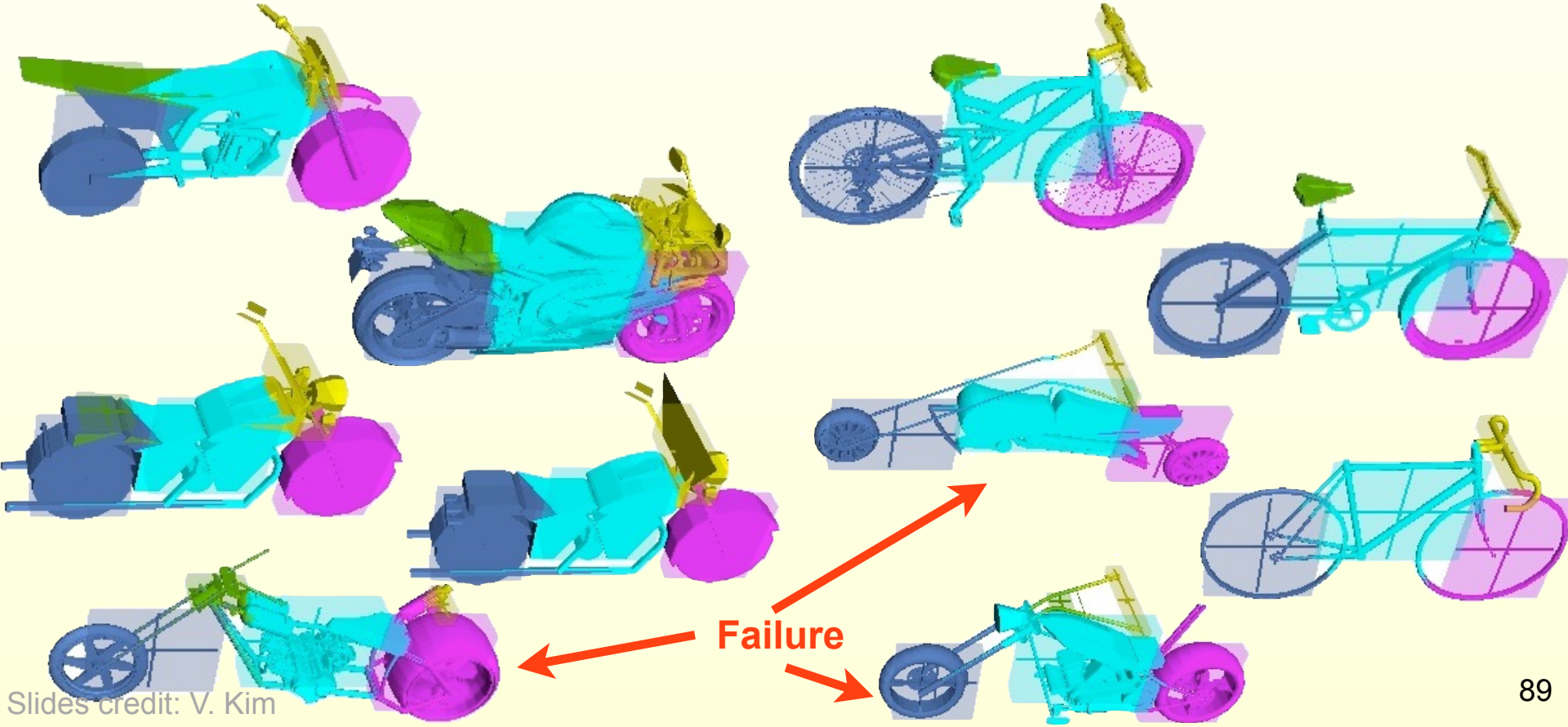
3D Warehouse: 471 bikes



378



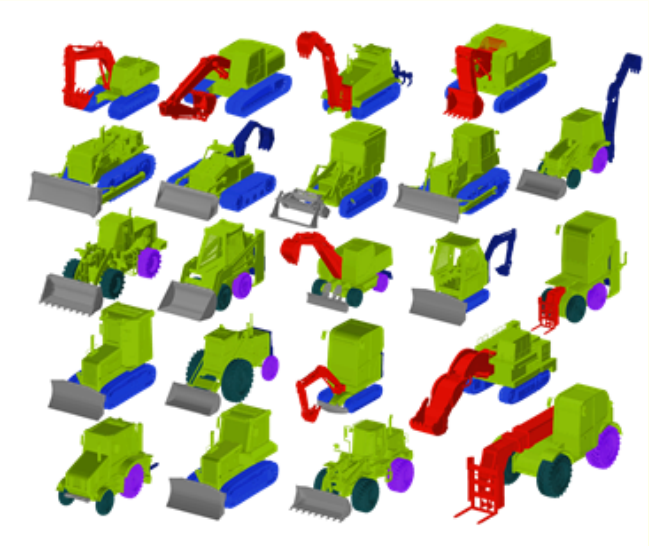
63

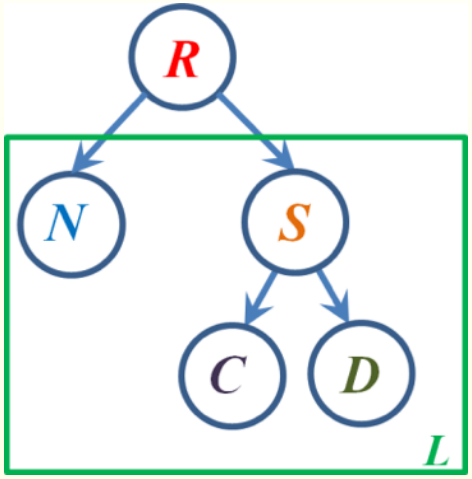


Slides credit: V. Kim

Learning a probabilistic model

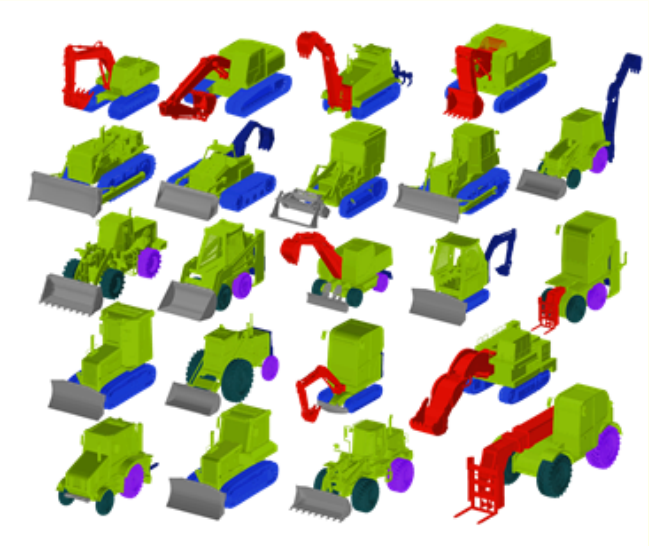
Learning a probabilistic model

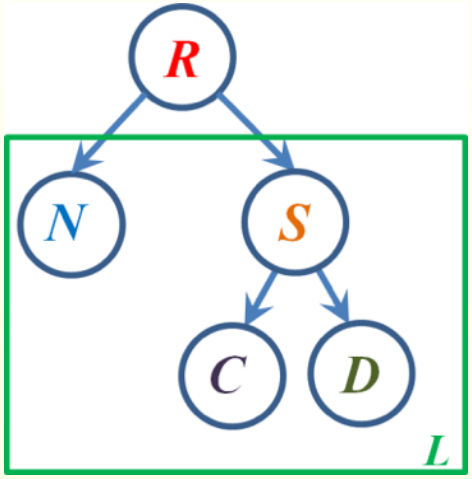




Slides credit: E. Kalogerakis

Learning a probabilistic model





Shape type

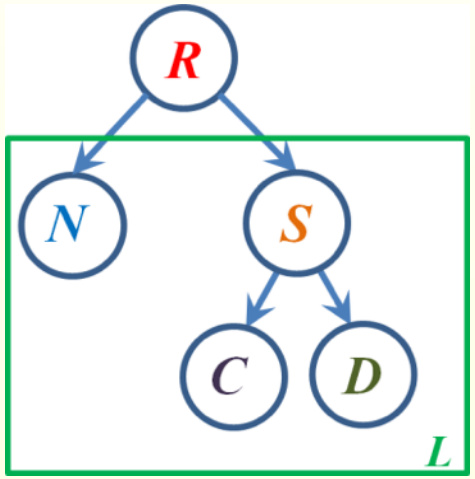
Component types

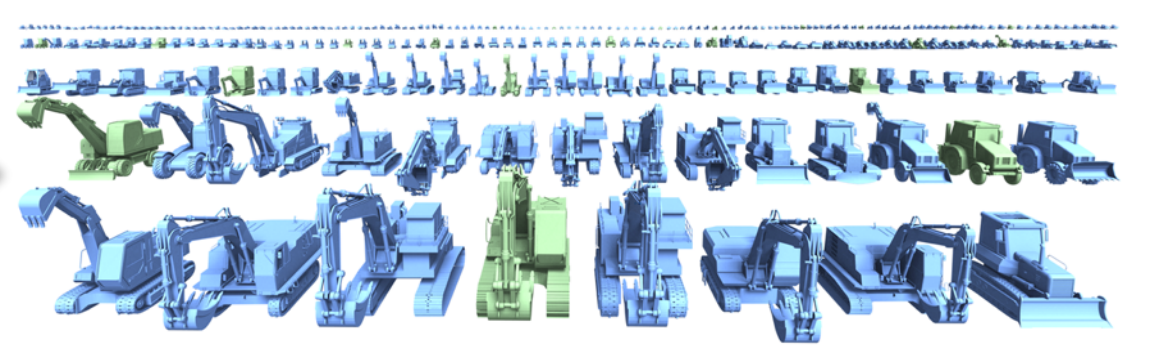
Number of components

Component geometry

$$P(R, S, N, G)$$

Synthesis stage

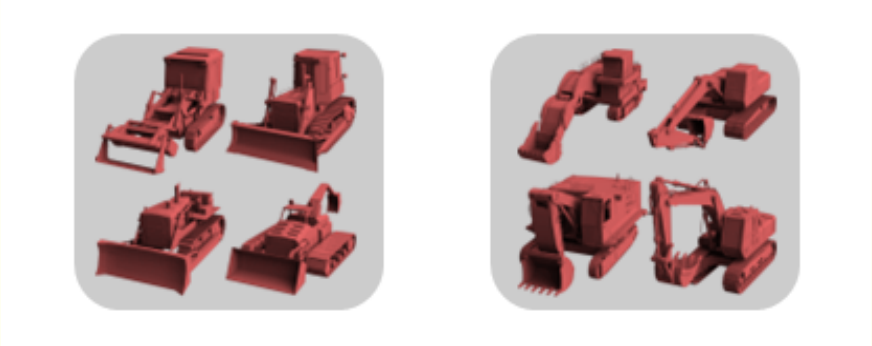




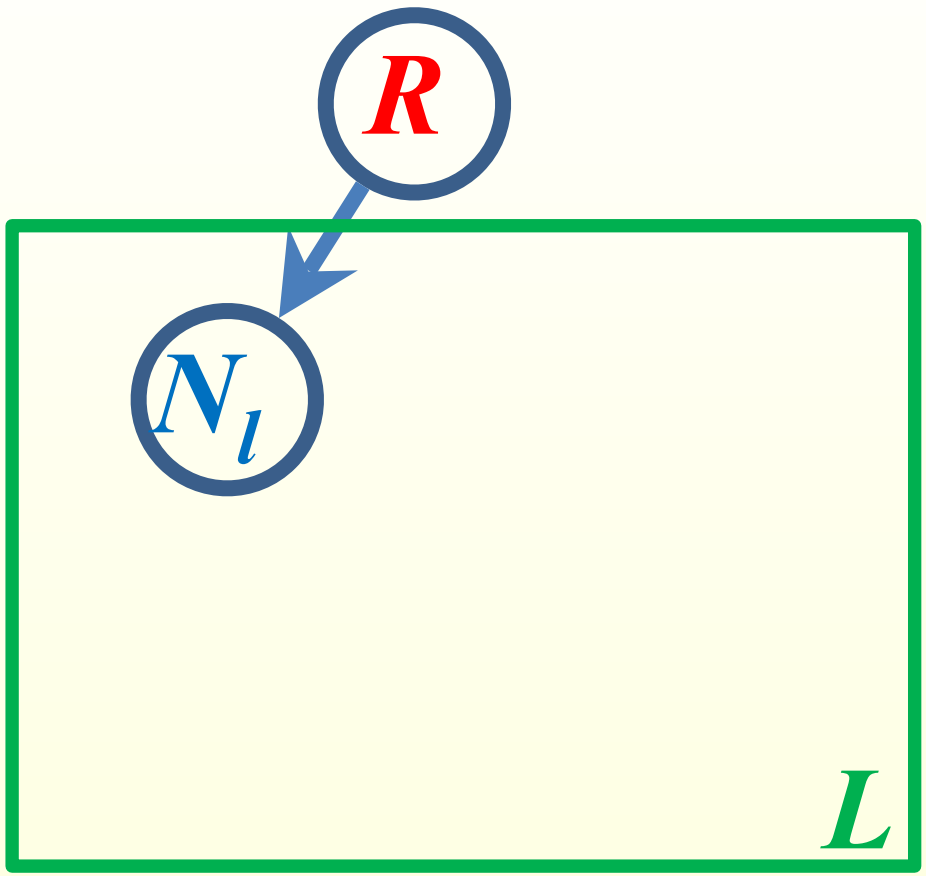
Slides credit: E. Kalogerakis

$\mathrm{P}(R)$

R

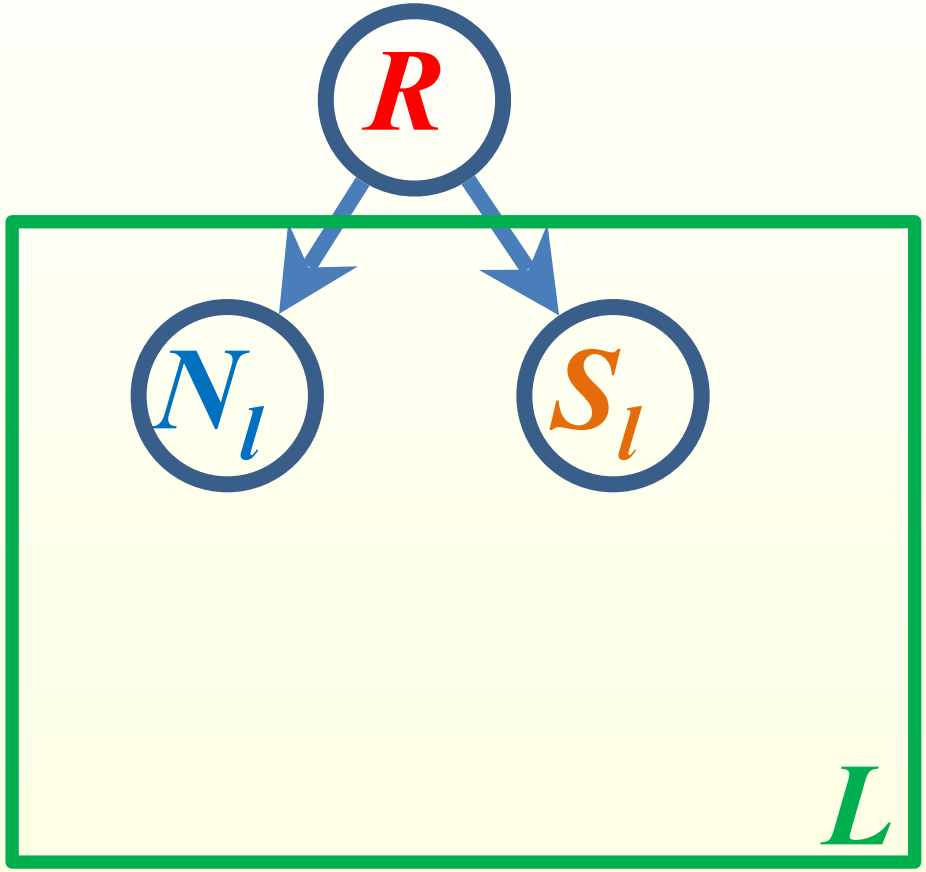


$\mathrm{P}(R)$



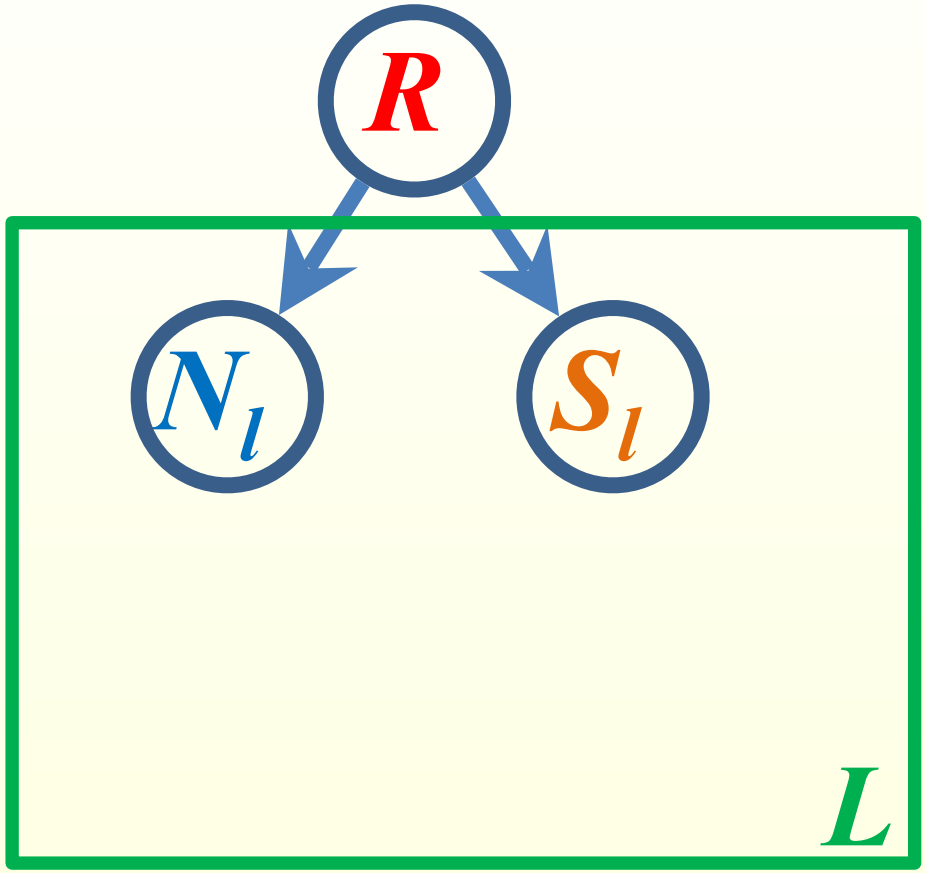
$$P(R) \prod_{l \in L} [P(N_l \mid R)]$$

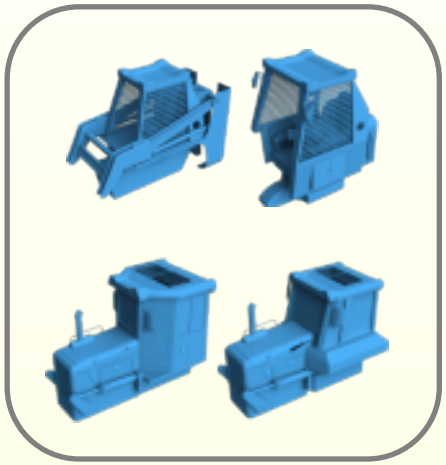
Slides credit: E. Kalogerakis

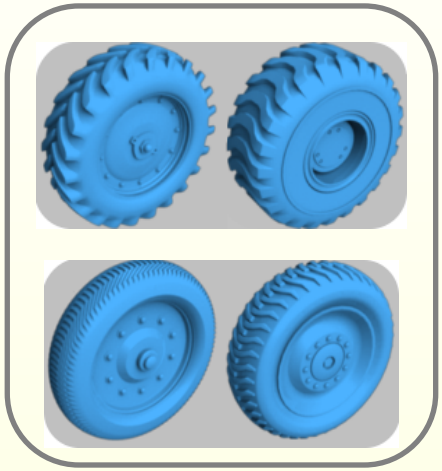


$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R) \right]$$

Slides credit: E. Kalogerakis

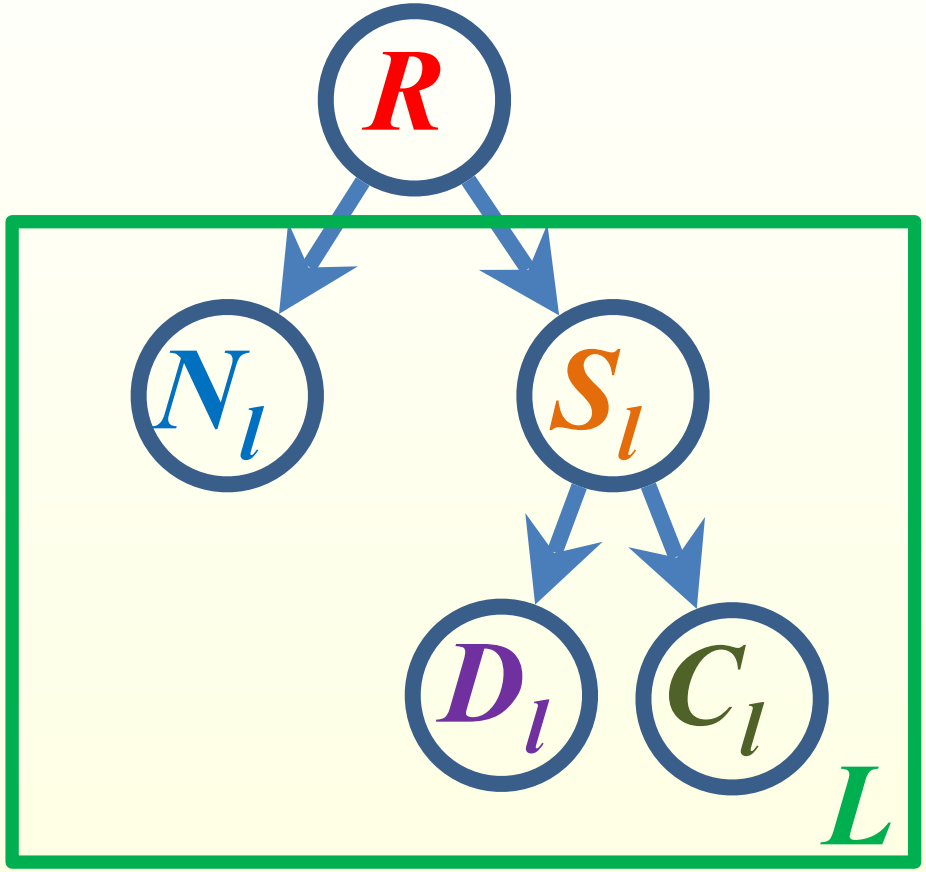






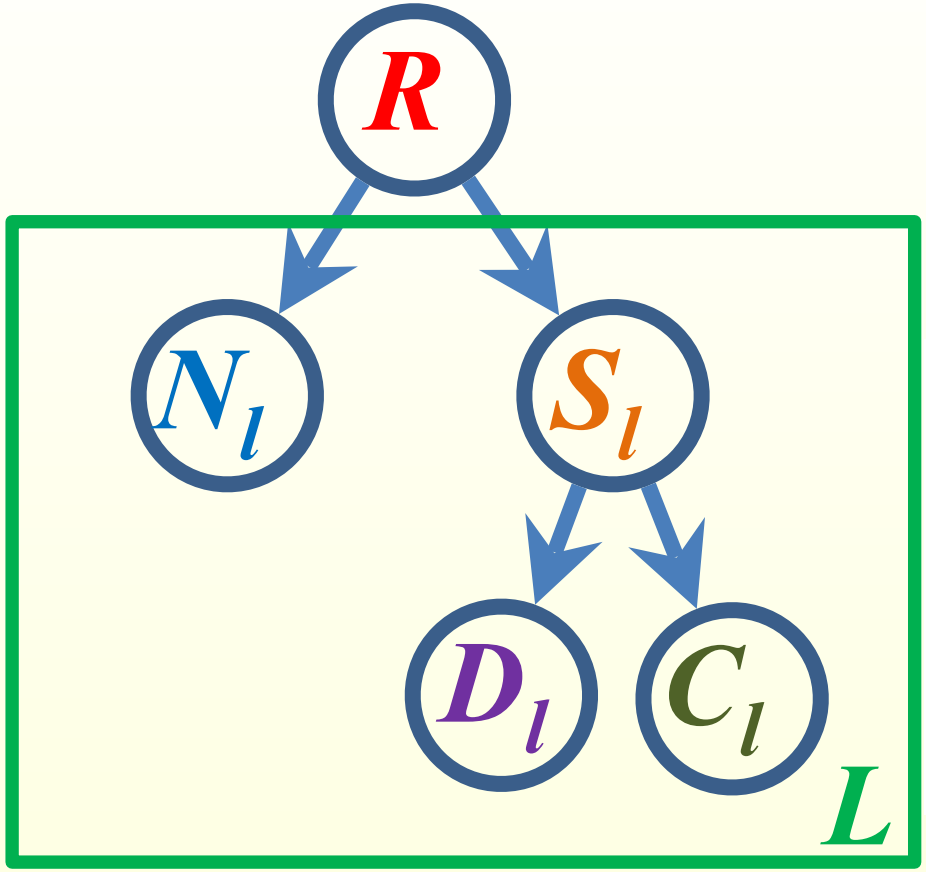
$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R) \right]$$

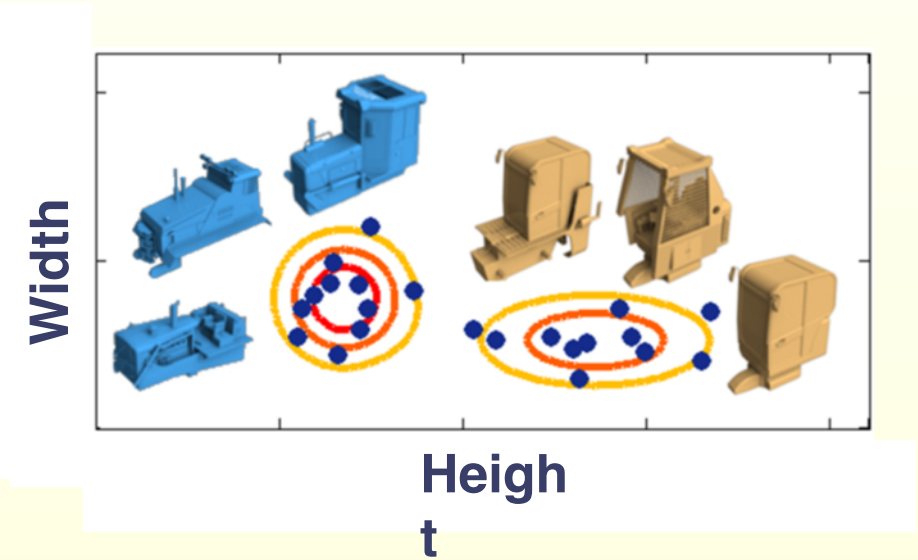
Slides credit: E. Kalogerakis



$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R)\, P(D_l \mid S_l)\, P(C_l \mid S_l) \right]$$

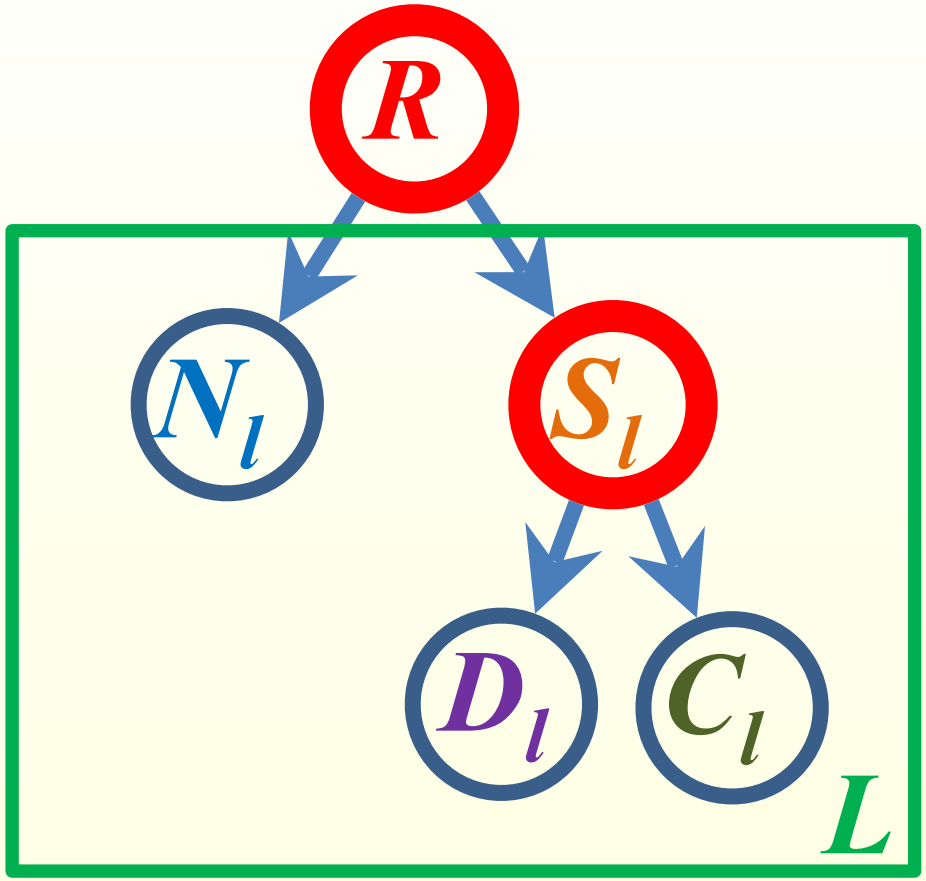
Slides credit: E. Kalogerakis





$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R)\, P(D_l \mid S_l)\, P(C_l \mid S_l) \right]$$

Slides credit: E. Kalogerakis

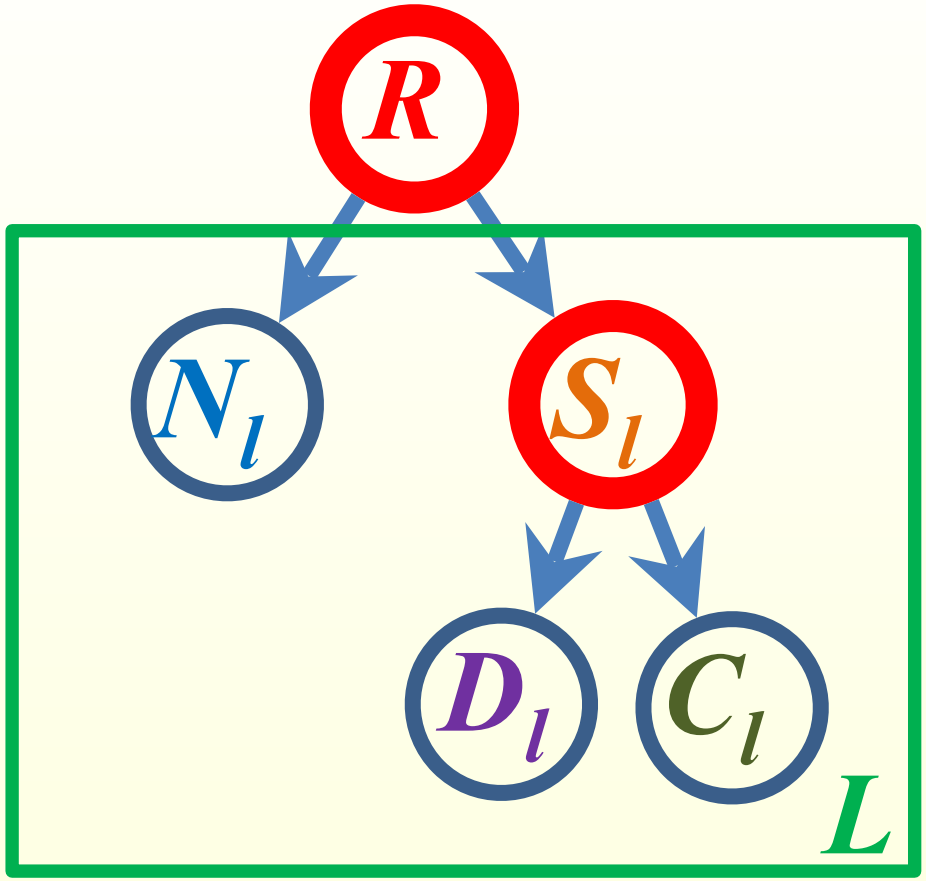


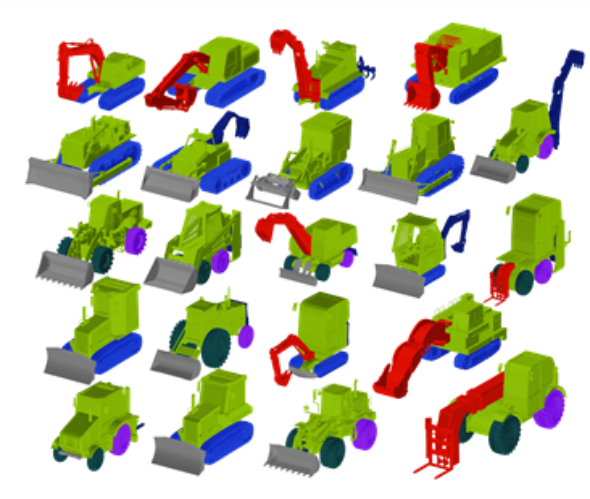
Latent object style

Latent component style

$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R)\, P(D_l \mid S_l)\, P(C_l \mid S_l) \right]$$

Slides credit: E. Kalogerakis





Learn from training data:

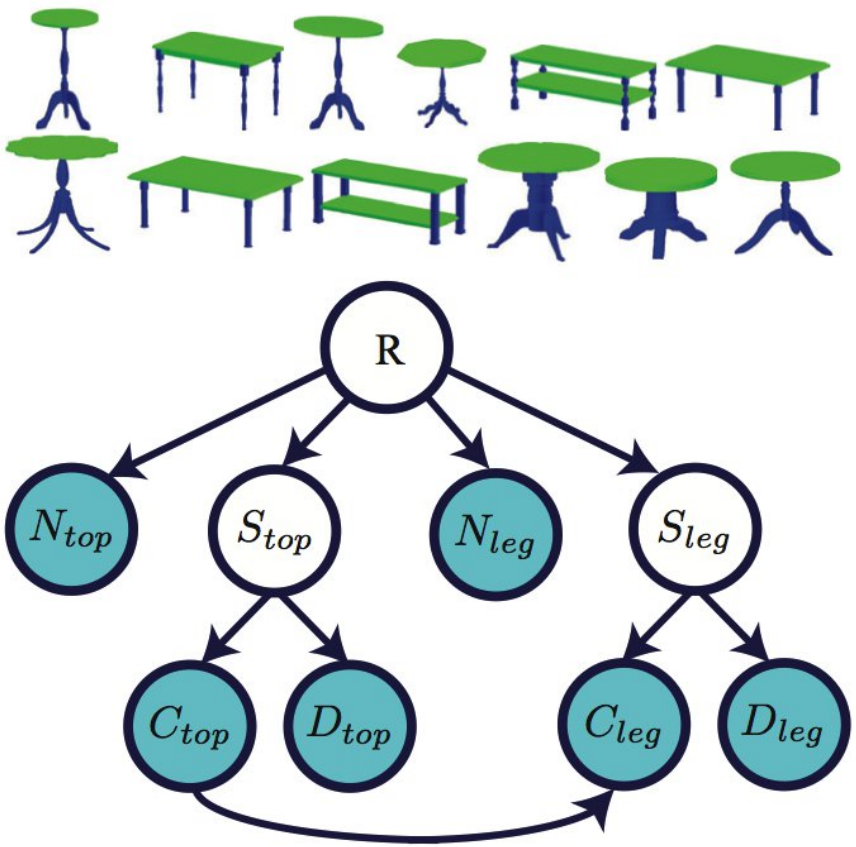
latent styles

lateral edges

parameters of CPDs

Slides credit: E. Kalogerakis

Example of obtained model



Slides credit: E. Kalogerakis

Learning

- Structure learning: given observed data **O**, find structure **G** that maximizes

$$P(G \mid \mathbf{O}) = \frac{P(\mathbf{O} \mid G)P(G)}{P(\mathbf{O})}$$

Slides credit: E. Kalogerakis

Learning

- Structure learning: given observed data **O**, find structure **G** that maximizes

$$P(G \mid \mathbf{O}) = \frac{P(\mathbf{O} \mid G)P(G)}{P(\mathbf{O})}$$

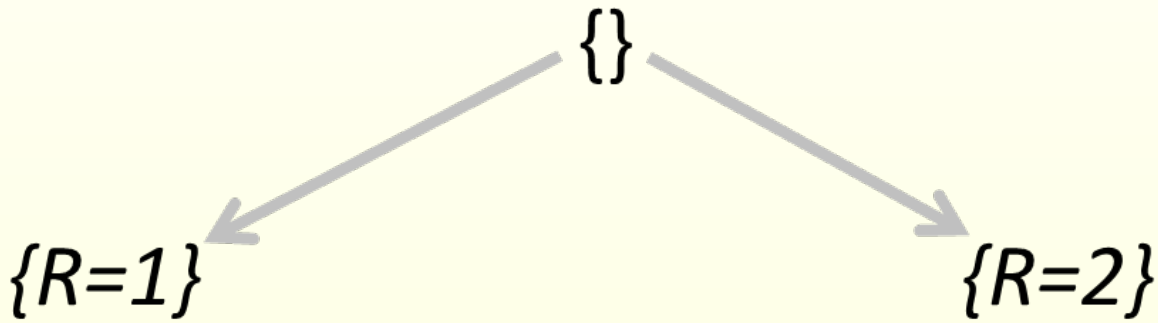
- Parameter learning: assuming uniform prior over structures, maximize **marginal likelihood**

$$P(\mathbf{O} \mid G) = \sum_{R,\mathbf{S}} \int P(\mathbf{O}, R, \mathbf{S} \mid \Theta, G) P(\Theta \mid G) \, \mathrm{d}\Theta$$

Slides credit: E. Kalogerakis

Shape synthesis

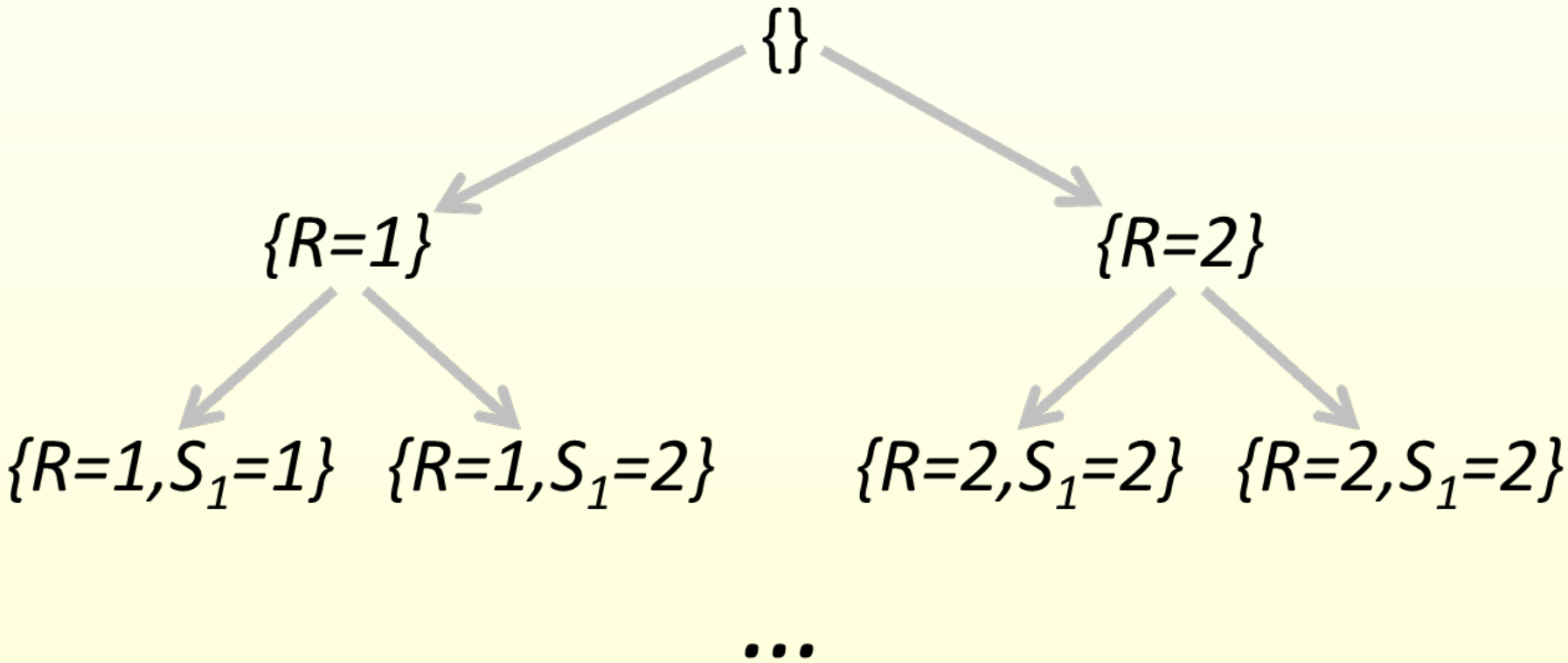
- Enumerate high-probability instantiations of the model



Slides credit: E. Kalogerakis

Shape synthesis

- Enumerate high-probability instantiations of the model



Slides credit: E. Kalogerakis

Component placement

Source shapes

Unoptimized new shape

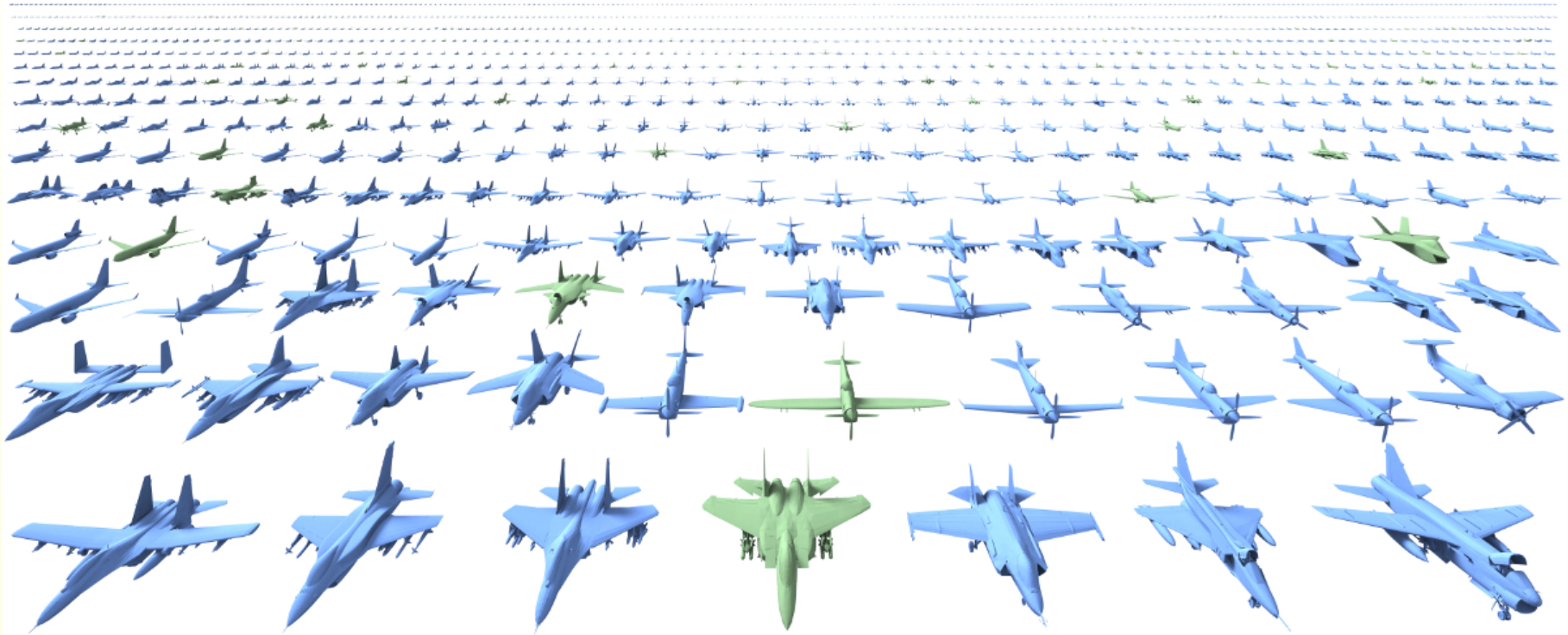
Optimized new shape

Slides credit: E. Kalogerakis

Database Amplification - Airplanes

Slides credit: E. Kalogerakis

Database Amplification - Airplanes

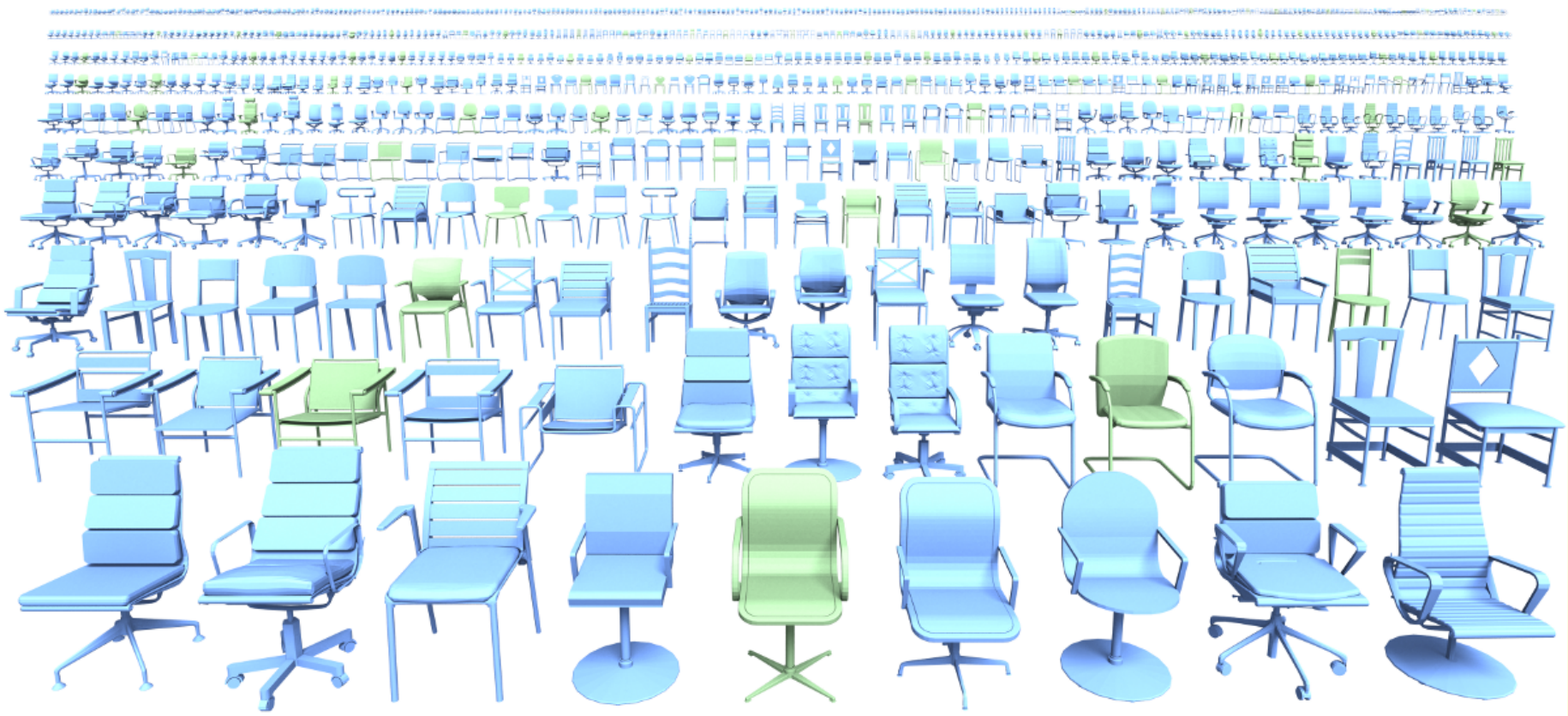


Slides credit: E. Kalogerakis

Database Amplification - Chairs

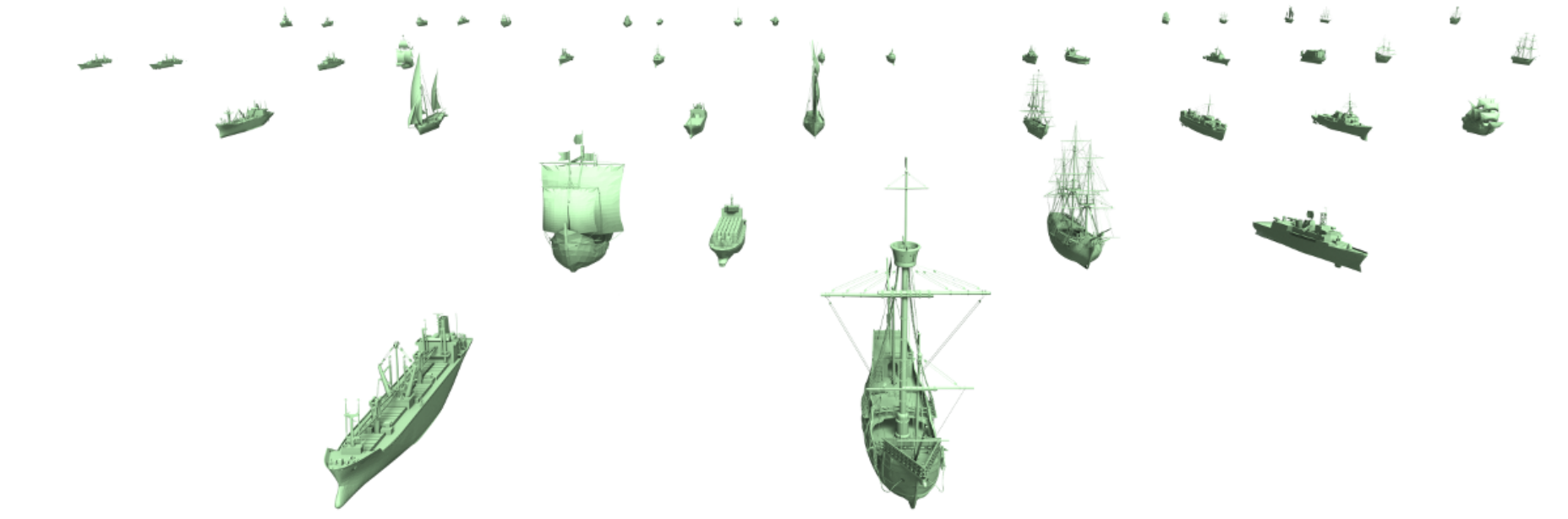
Slides credit: E. Kalogerakis

Database Amplification - Chairs



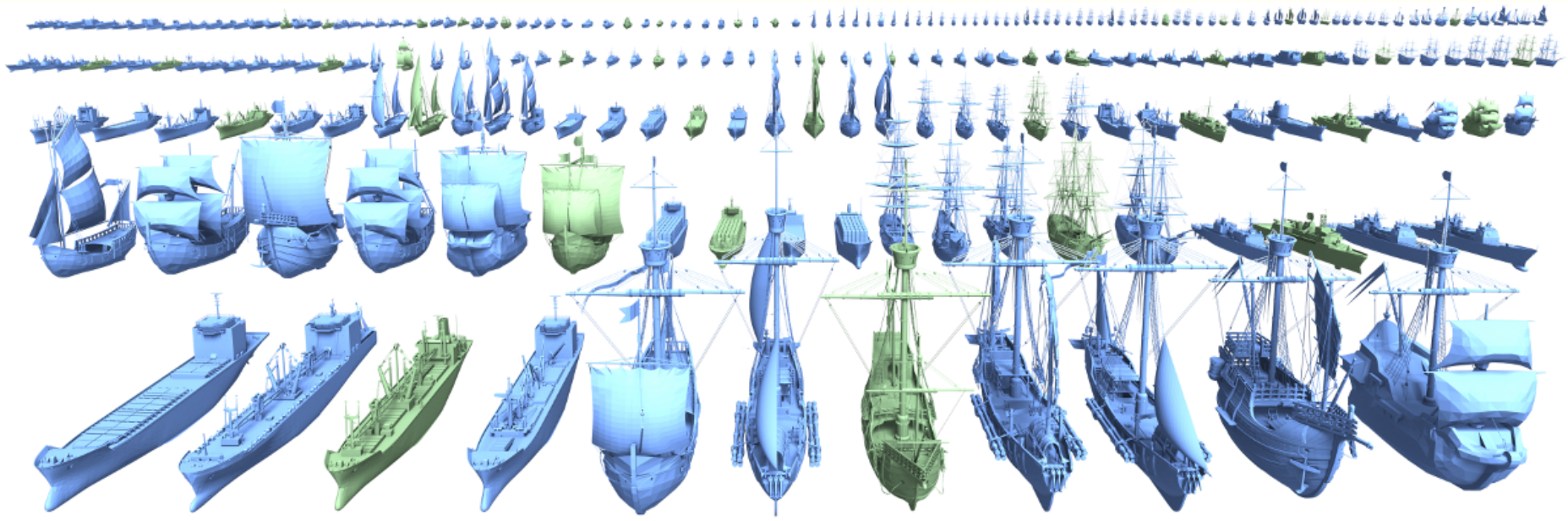
Slides credit: E. Kalogerakis

Database Amplification - Ships



Slides credit: E. Kalogerakis

Database Amplification - Ships

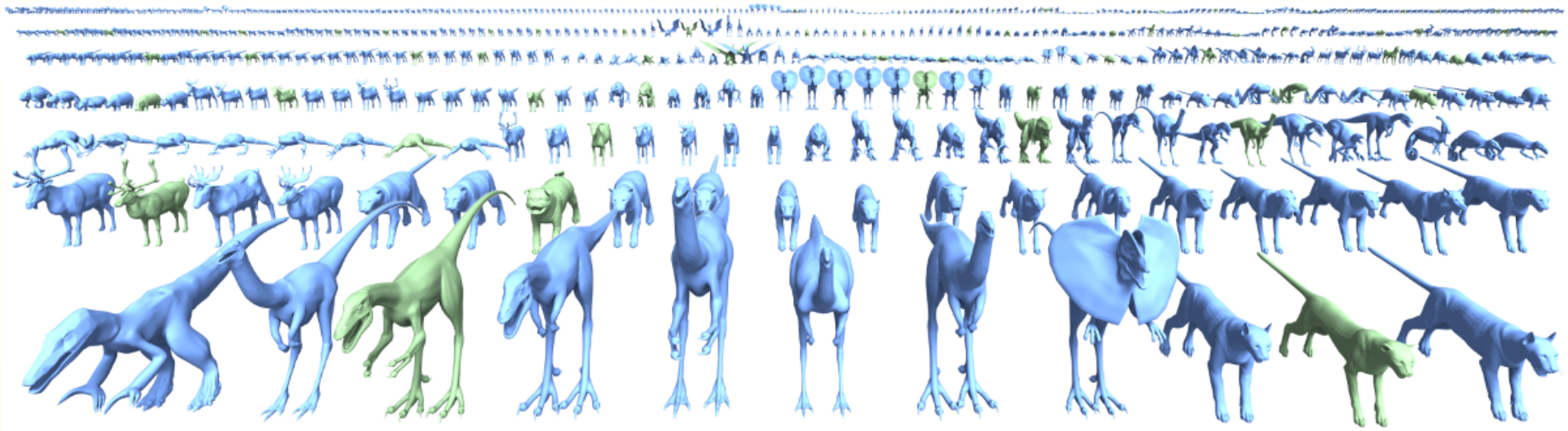


Slides credit: E. Kalogerakis

Database Amplification - Animals

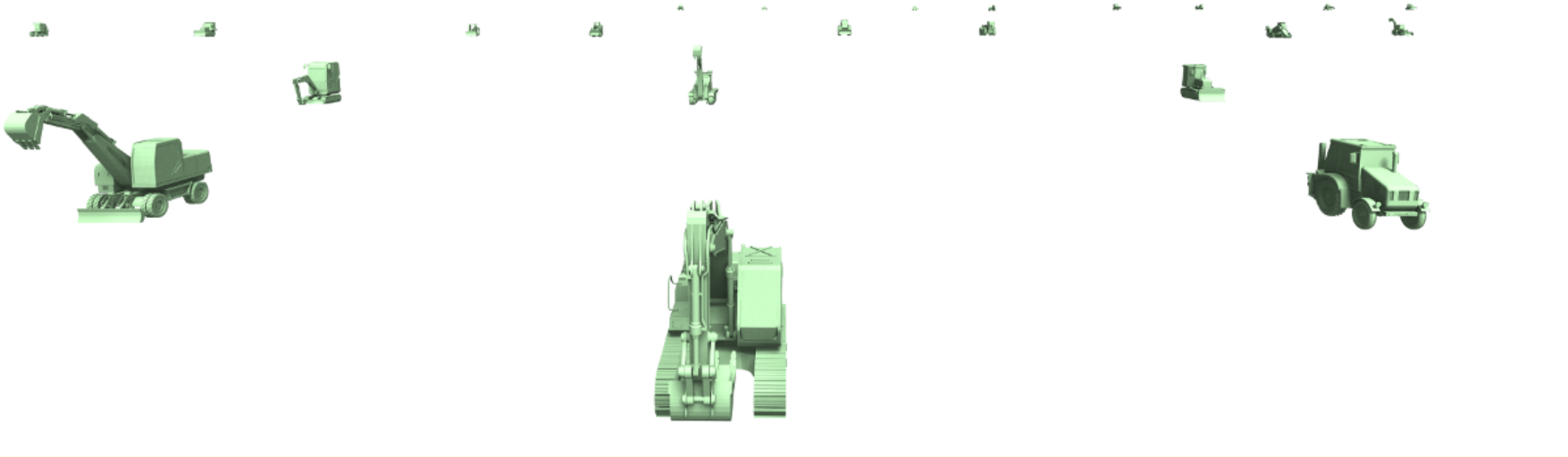
Slides credit: E. Kalogerakis

Database Amplification - Animals



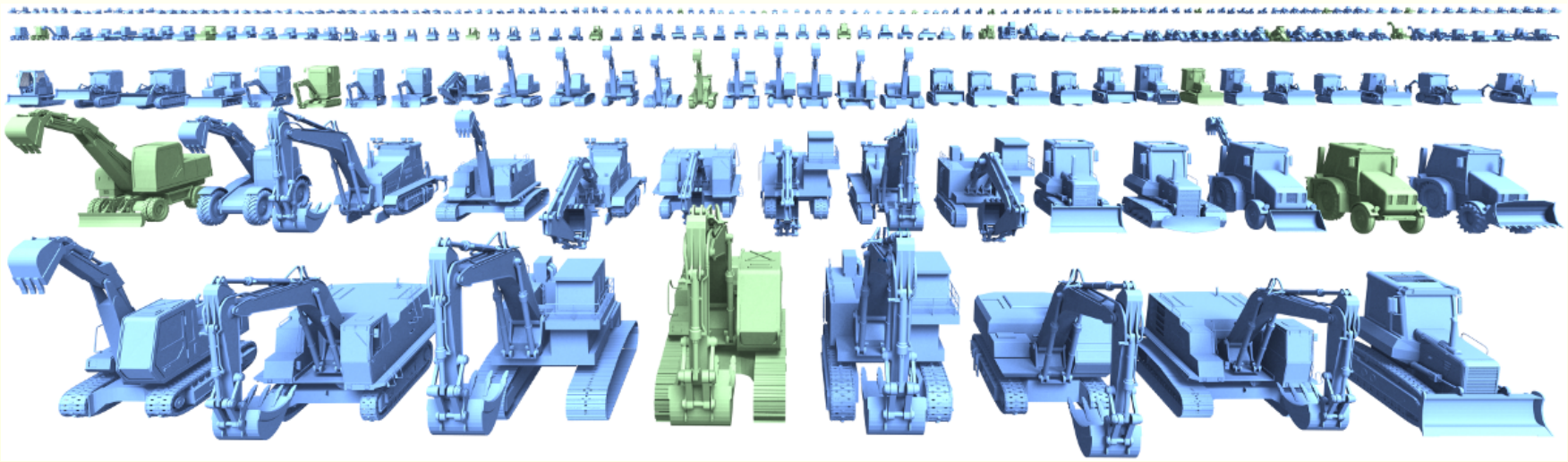
Slides credit: E. Kalogerakis

Database Amplification – Construction vehicles



Slides credit: E. Kalogerakis

Database Amplification – Construction vehicles



Slides credit: E. Kalogerakis

References

- A Morphable Model for the Synthesis of 3D Faces.
  Volker Blanz and Thomas Vetter. SIGGRAPH 1999
- The space of human body shapes: reconstruction and parameterization from range scans.
  B. Allen, B. Curless, Z. Popovic. SIGGRAPH 2003
- SCAPE: shape completion and animation of people.
  D. Anguelov, P. Srinivasan, D. Koller, S. Thrun, J. Rodgers, J. Davis. SIGGRAPH 2005.
- Learning Part-based Templates from Large Collections of 3D Shapes.
  V. G. Kim, W. Li, N. J. Mitra, S. Chaudhuri, S. DiVerdi, and T. Funkhouser. SIGGRAPH 2013
- A Probabilistic Model for Component-Based Shape Synthesis.
  E. Kalogerakis, S. Chaudhuri, D. Koller, V. Koltun. SIGGRAPH 2012

THE END