Probabilistic Reasoning for Assembly-Based 3D Modeling

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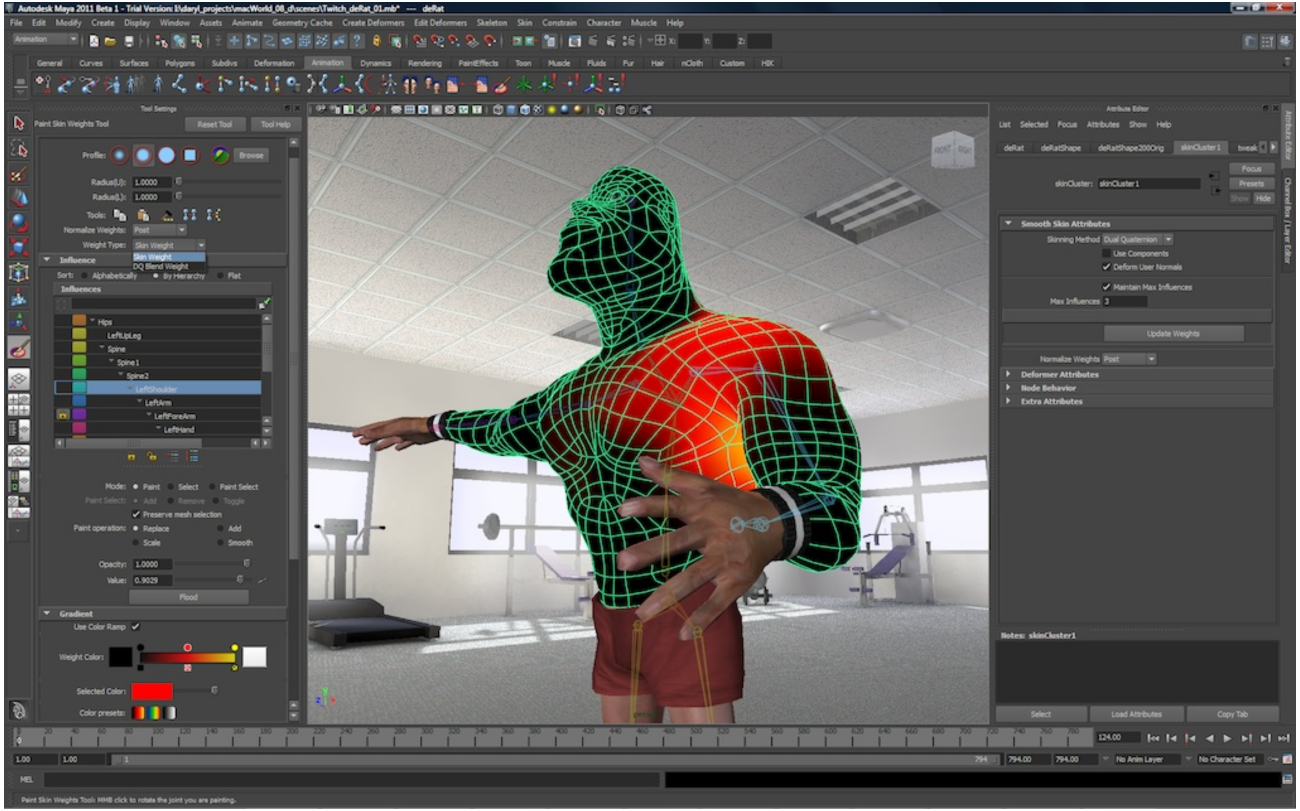
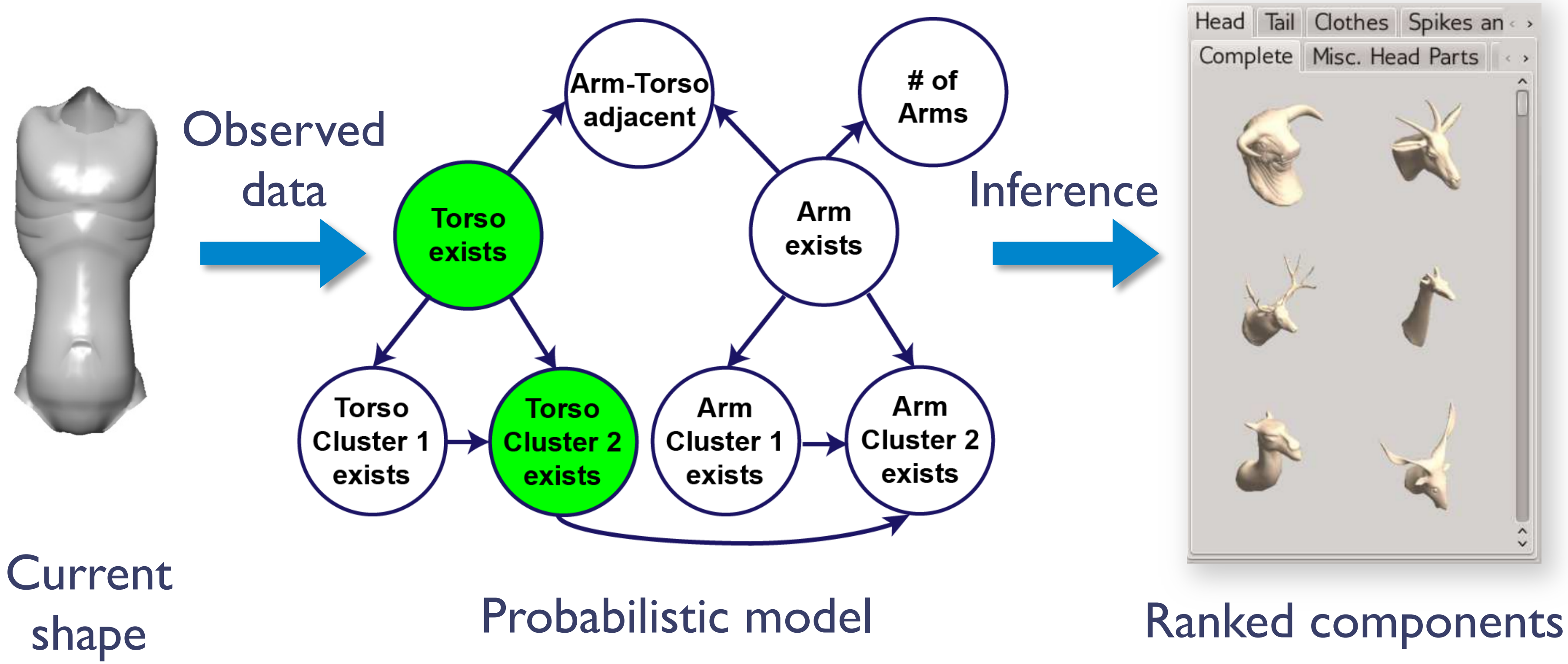
Stanford University

Creating detailed 3D content is hard

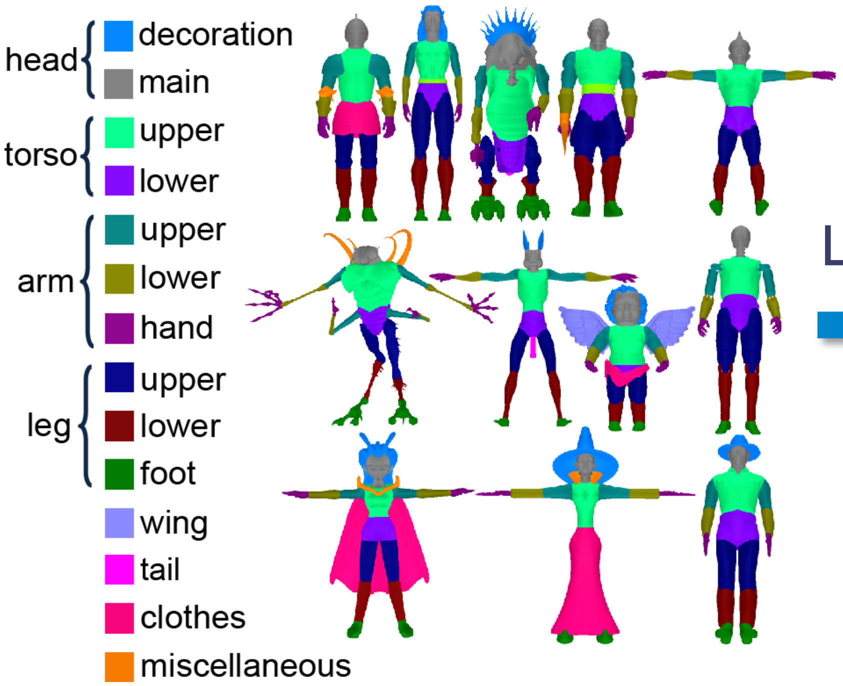



Modeling by Assembly
File
Edit
View
Torso
Head
Leg
Tail
Arm
Complete
Lower Torso
Uppe
Text search
Search
2x speed

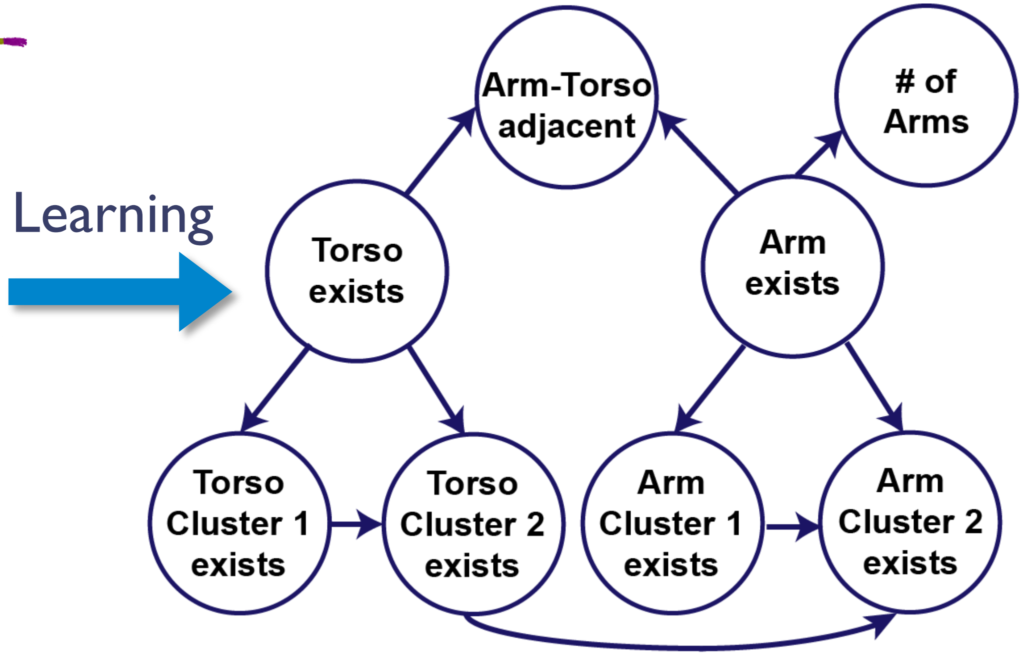
Probabilistic model for presenting relevant components



The model is learned from an input shape repository



Input repository



Probabilistic model

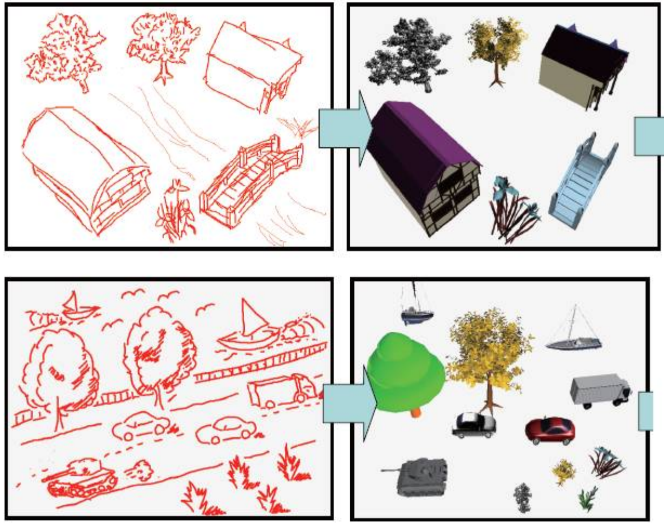
Related work: assembly-based 3D modeling

- Modeling by example [Funkhouser *et al.* 2004]

Related work: assembly-based 3D modeling

- Sketch-based retrieval of components

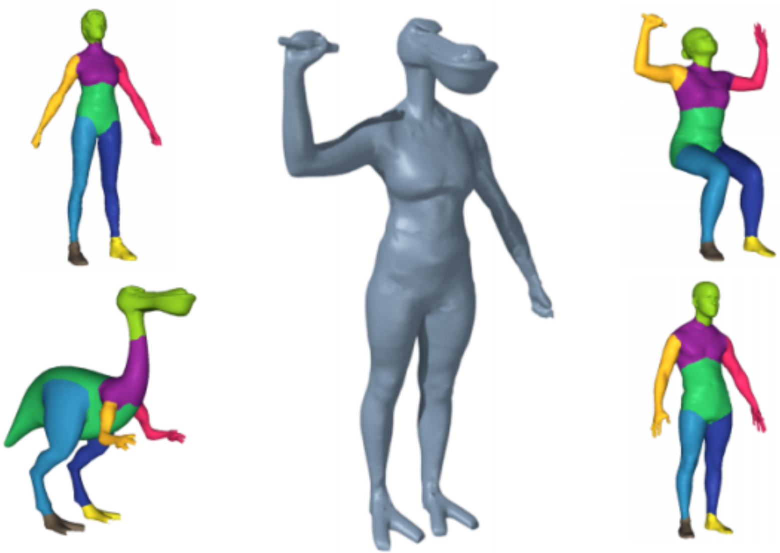
[Shin and Igarashi 2007] & [Lee and Funkhouser 2008]



Related work: assembly-based 3D modeling

- Model Composition from Interchangeable Components

[Kraevoy et al. 2007]



Related work: Spore [Maxis Software 2008]

Related work: Data-driven suggestions

Creativity support in 3D modeling [Chaudhuri and Koltun 2010]

Related work: Data-driven suggestions

Creativity support in 3D modeling [Chaudhuri and Koltun 2010]

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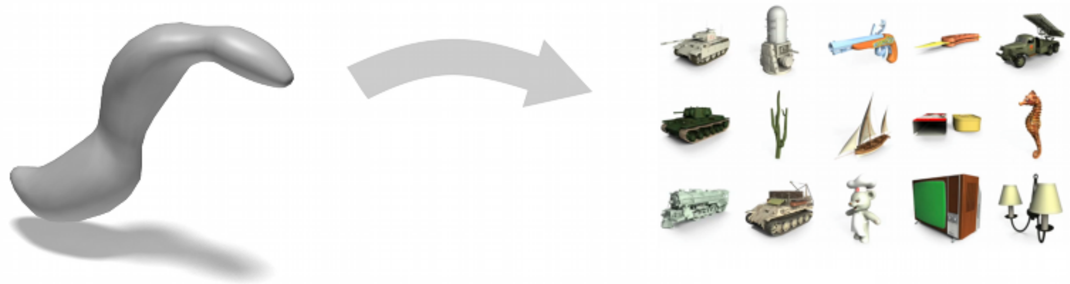
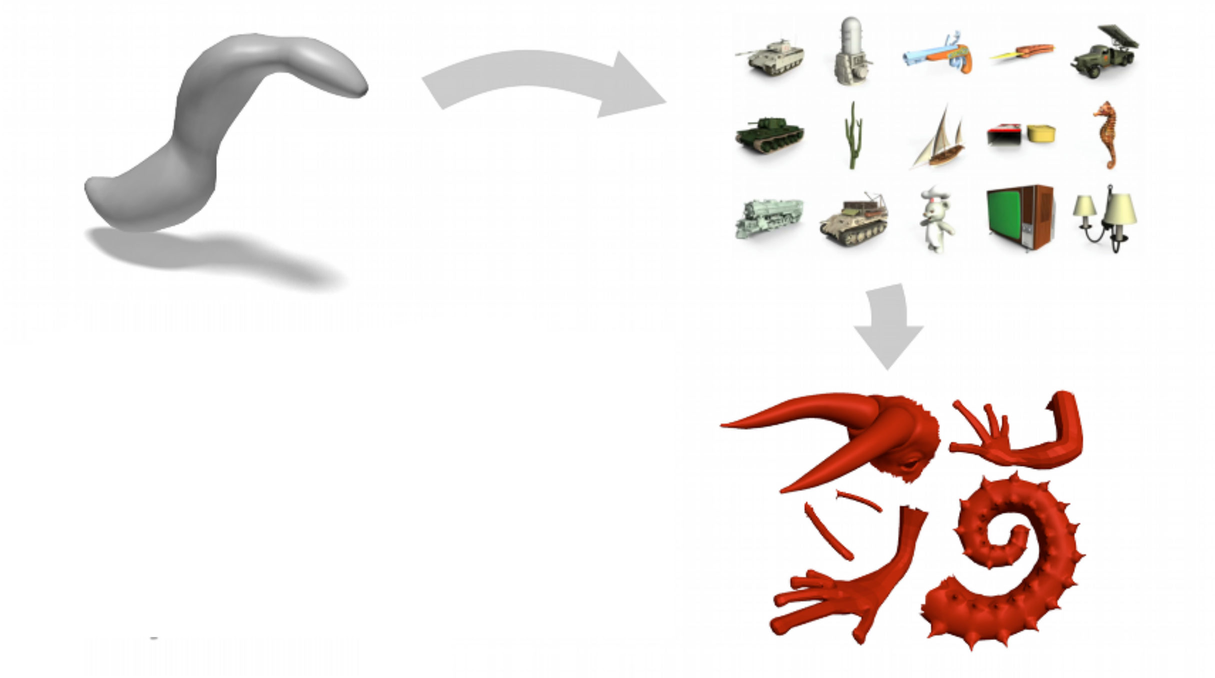


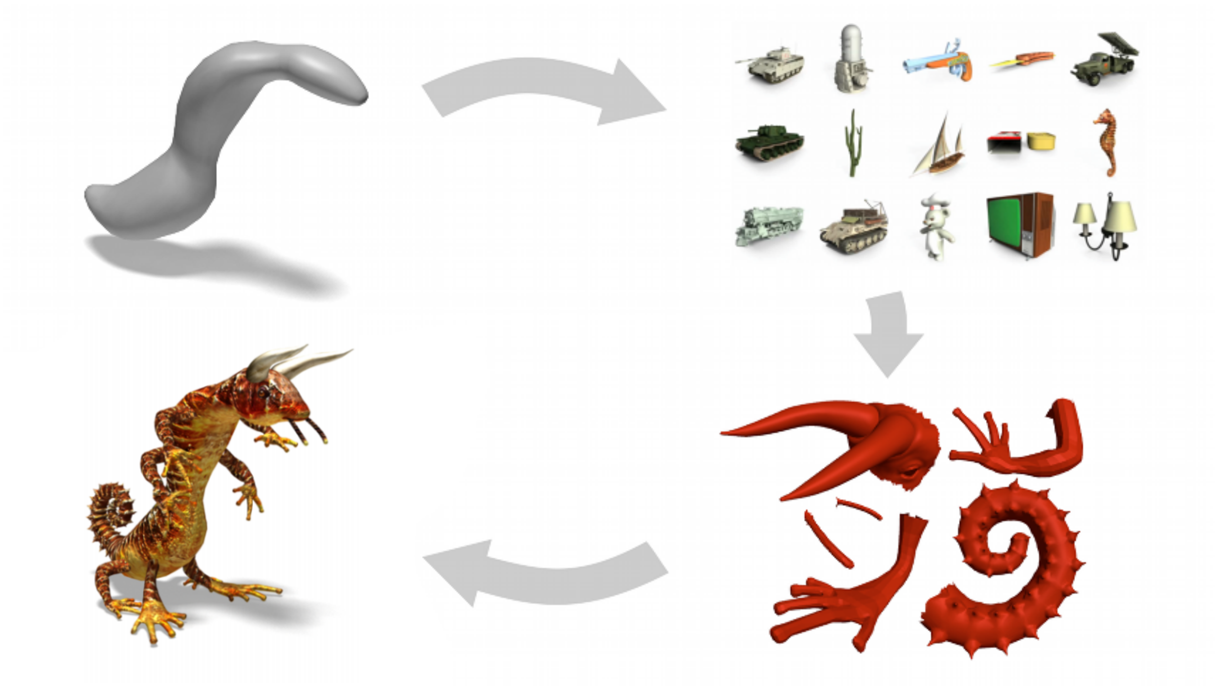
Related work: Data-driven suggestions

Creativity support in 3D modeling [Chaudhuri and Koltun 2010]

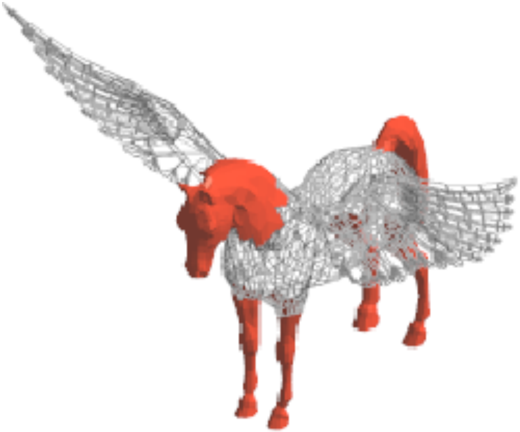


Related work: Data-driven suggestions

Creativity support in 3D modeling [Chaudhuri and Koltun 2010]



Should suggestions be agnostic to the structure of shapes being modeled?



Our probabilistic model

- Represents both **semantic** and **geometric** relationships
- **Learned automatically** from a shape database
- **Interactive suggestions** of components
- **Increases relevance** of presented components

Outline

1. **Probabilistic model definition**
2. Learning
3. Inference
4. Results

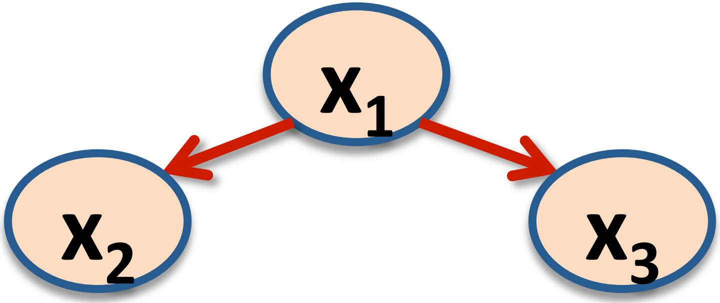
Our probabilistic model: a Bayesian Network

Shape attributes → Random variables $\boldsymbol{X} = \{x_i\}$

Dependencies between attributes → $P(\boldsymbol{X}) = \prod_i P\left(x_i \mid parents(x_i)\right)$

Represent with DAG

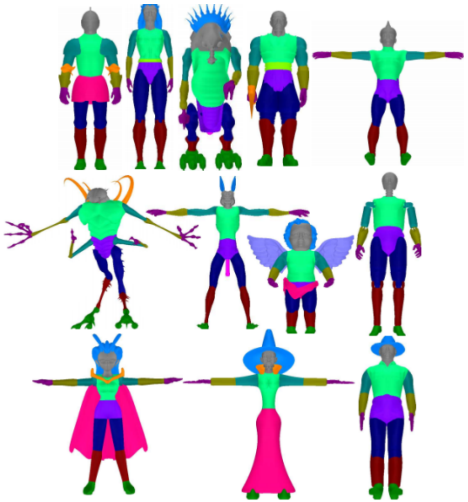
$$P(\boldsymbol{X}) = P(x_1)P(x_2 \mid x_1)P(x_3 \mid x_1)$$



Random variables E_l

Existence of component from category l

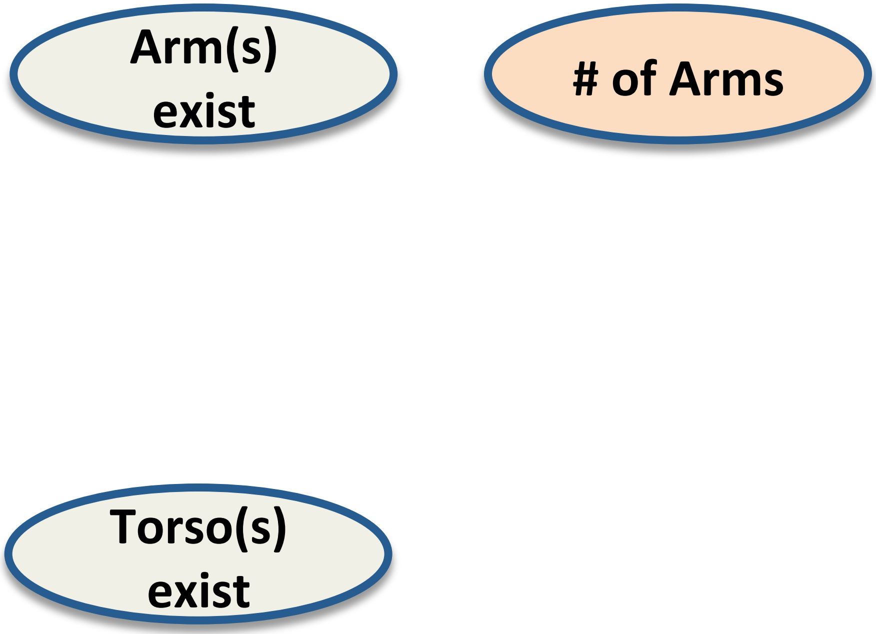
Arm(s) exist



Torso(s) exist

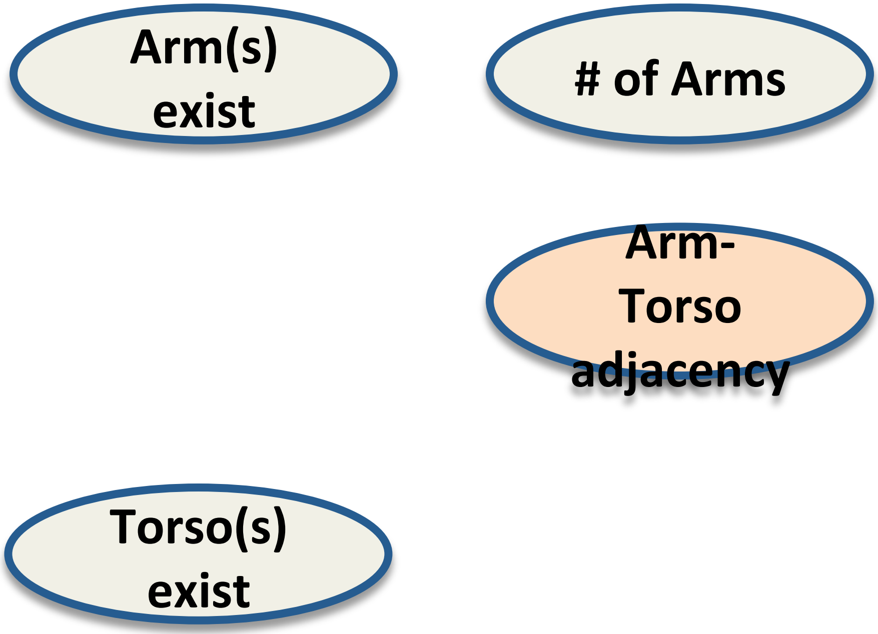
Random variables N_l

Number of components from category l



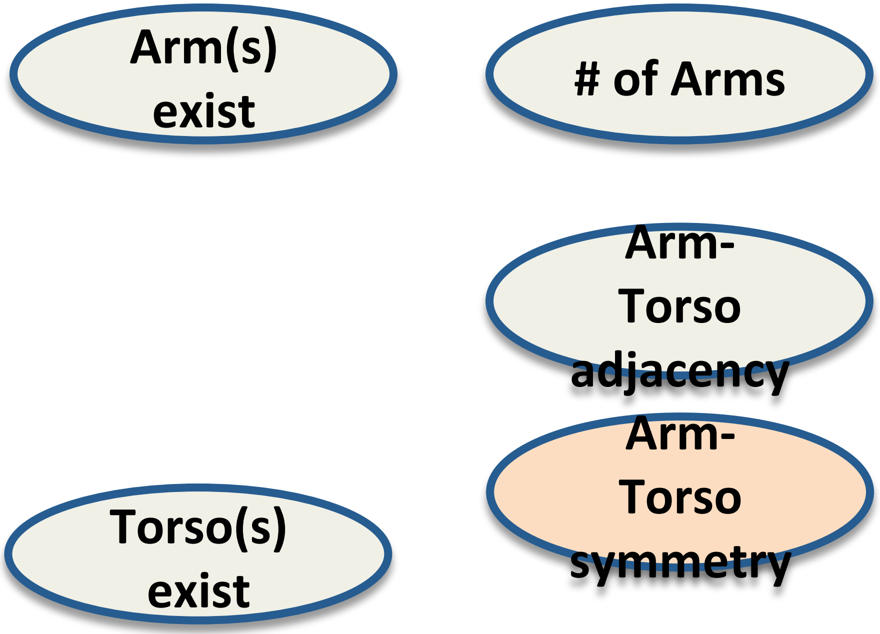
Random variables $A_{l,l'}$

Adjacency between components from categories l and l'



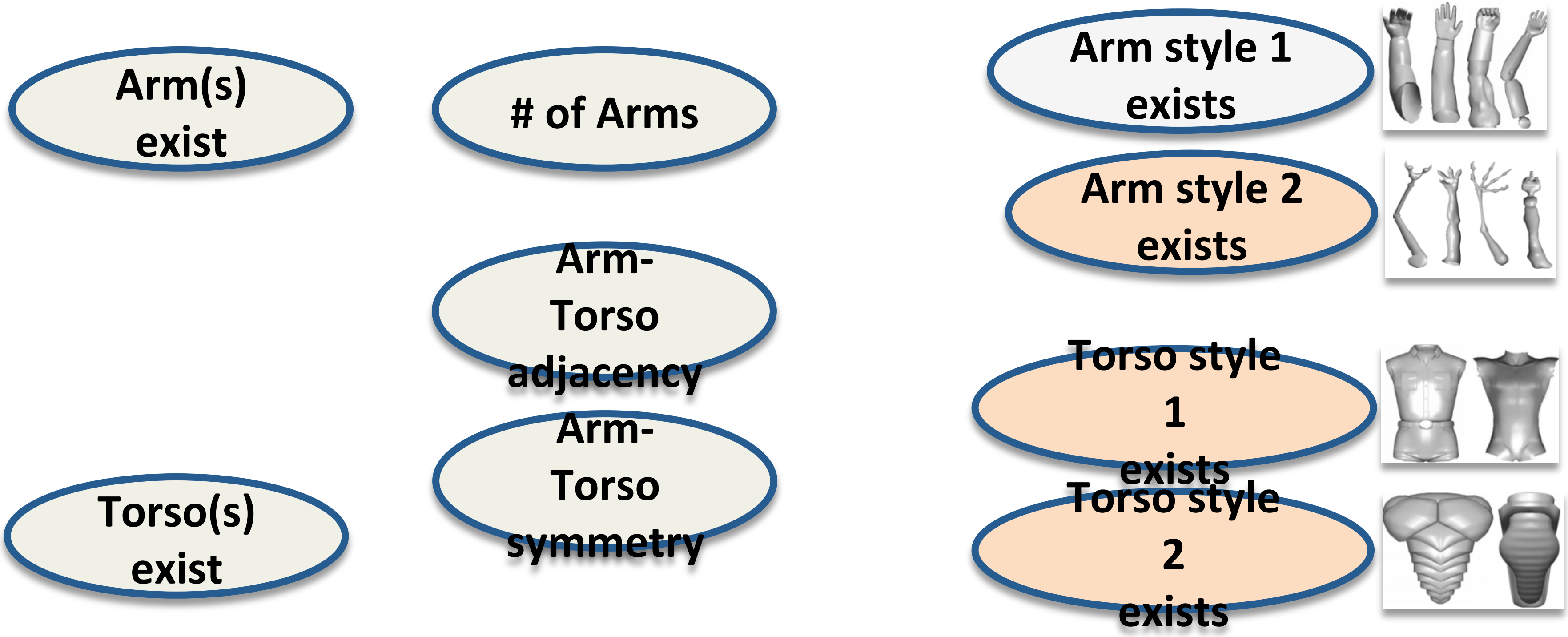
Random variables $R_{l,l'}$

Symmetry relation between components from categories l and l'

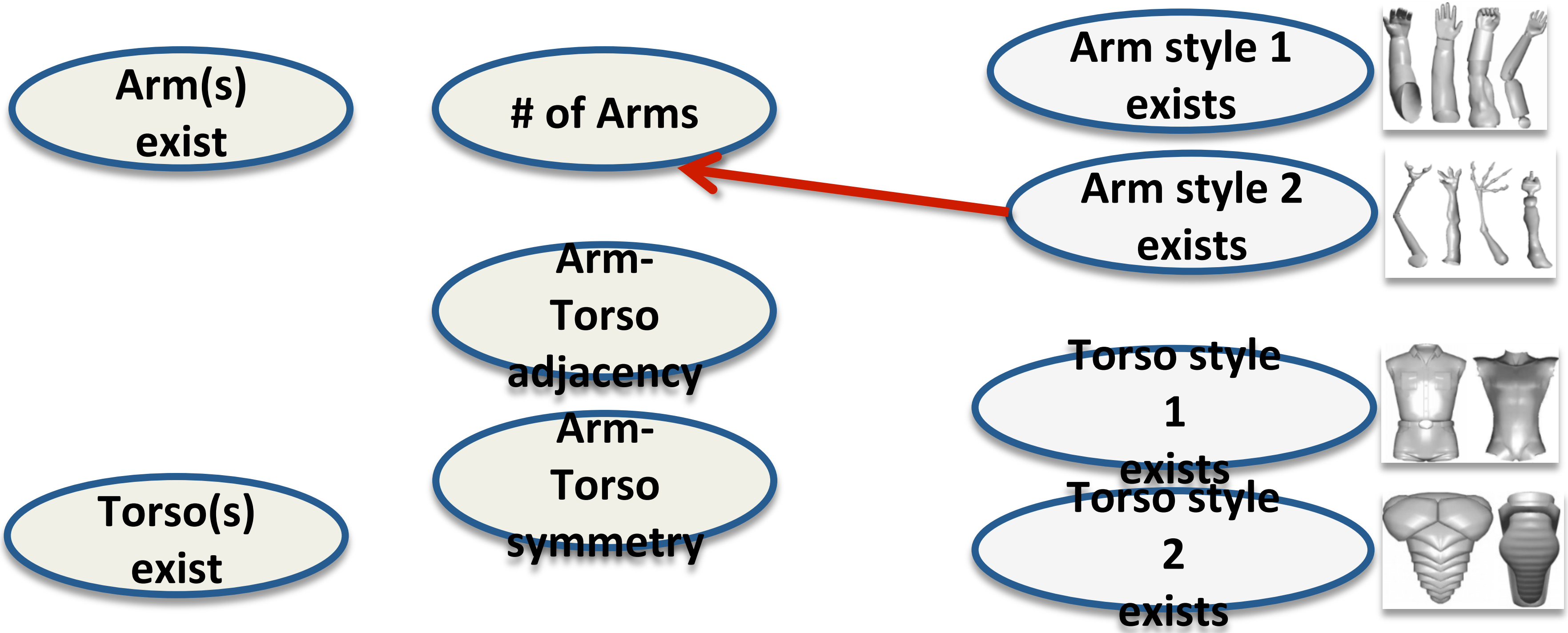


Random variables $S_{s,l}$

Existence of component from style cluster s of category l

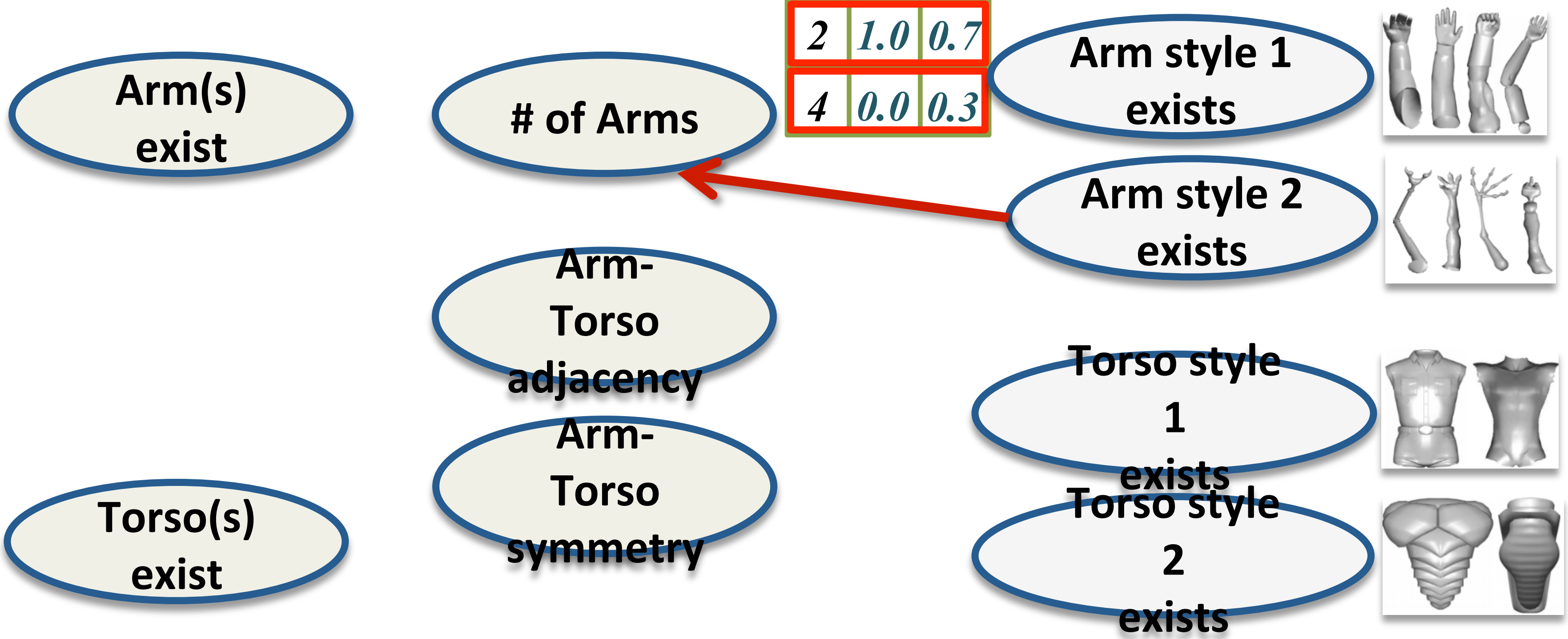


Dependencies between random variables

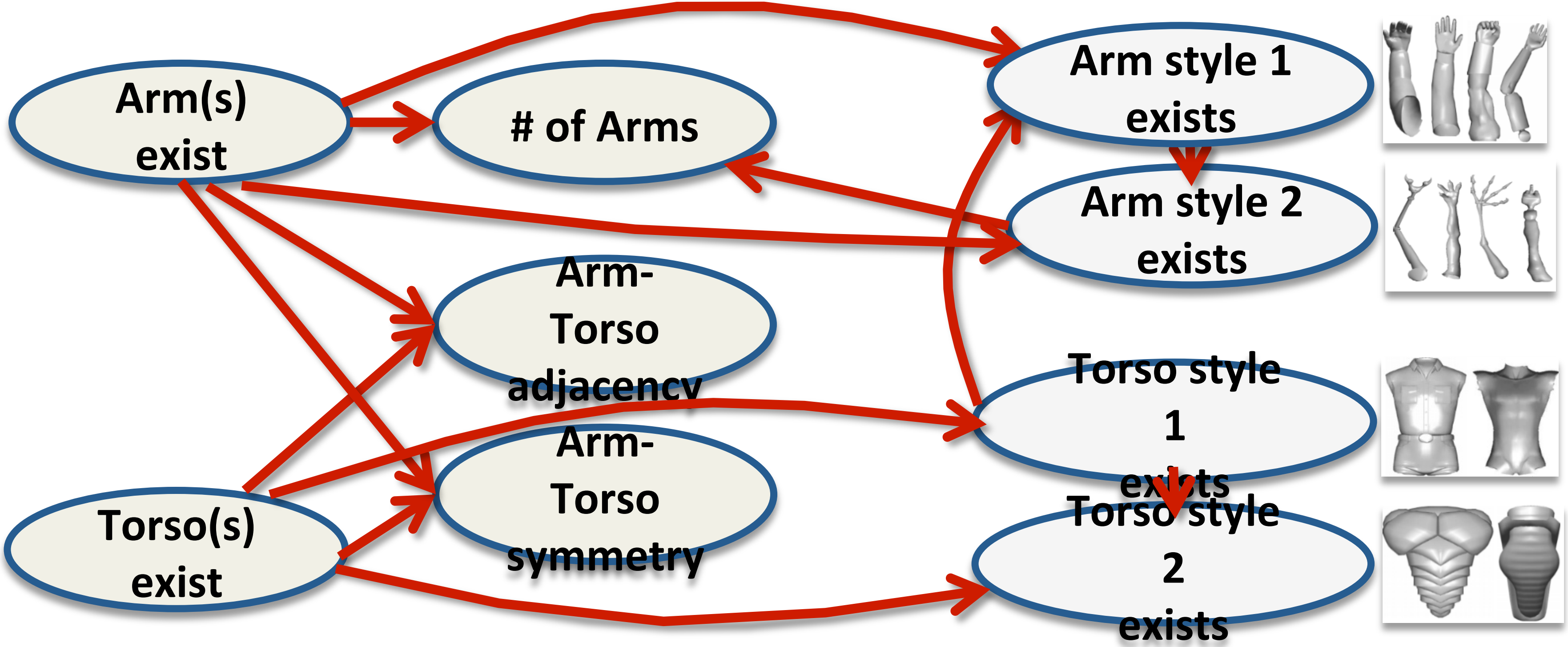


Conditional probability tables

N_l \ R_l	*0*	*1*
2	*1.0*	*0.7*
4	*0.0*	*0.3*



Dependencies between random variables



Outline

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2. **Learning**
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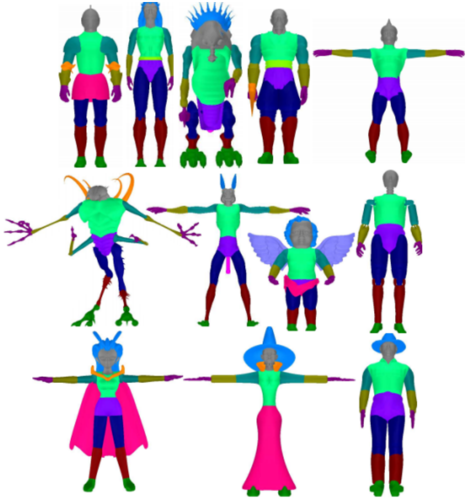
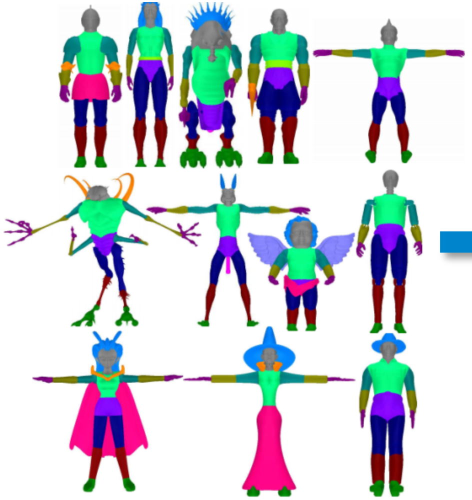
Learning the CPTs and the graph structure



[Kalogerakis et al. 2010]
(modified)

Learning the CPTs and the graph structure



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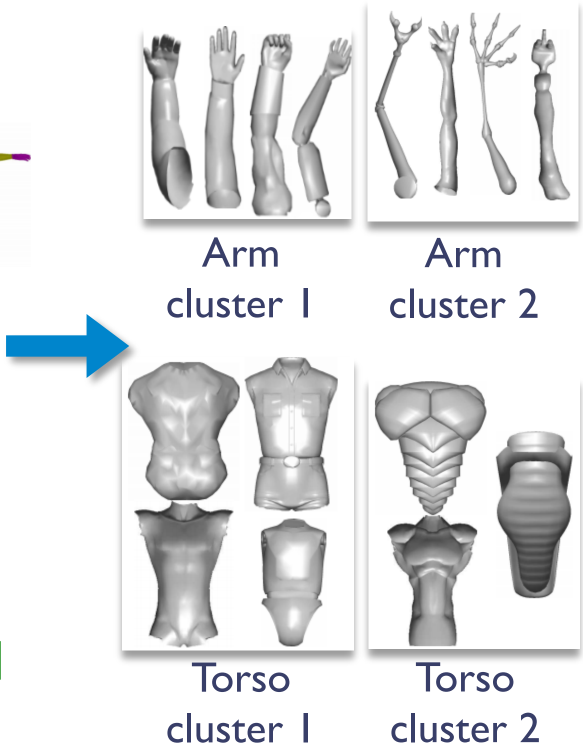
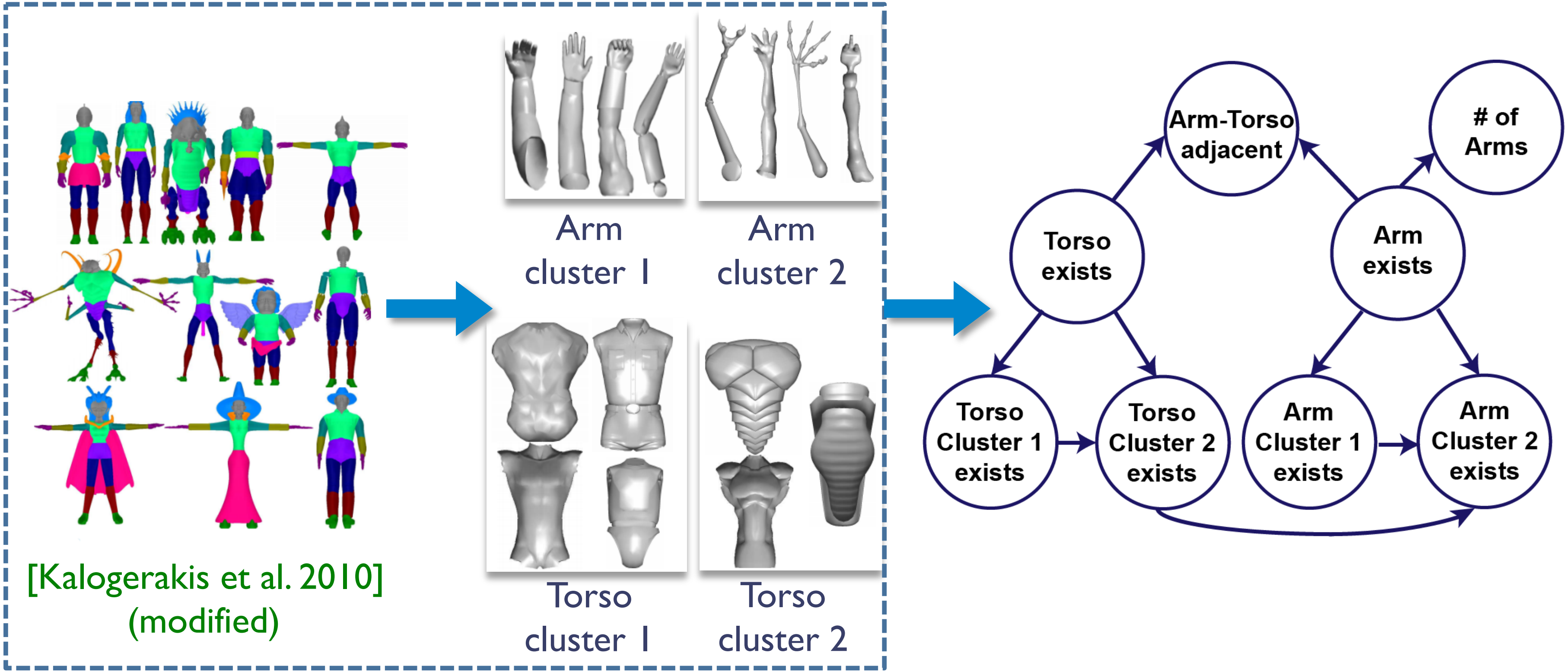


Learning the CPTs and the graph structure



Structure and parameter learning

Maximize Bayesian Information Criterion

$$BIC = \log P(D \mid G, \boldsymbol{\theta}) - \frac{1}{2} v \log n$$

Structure and parameter learning

Maximize Bayesian Information Criterion

$$BIC = \boxed{\log P(D \mid G, \boldsymbol{\theta})} - \frac{1}{2} v \log n$$

Likelihood term

D: training data

G: graph structure

θ: CPT entries

Structure and parameter learning

Maximize Bayesian Information Criterion

$$BIC = \log P(D \mid G, \boldsymbol{\theta}) - \boxed{\frac{1}{2} v \log n}$$

Penalize model complexity

v: # of independent CPT entries

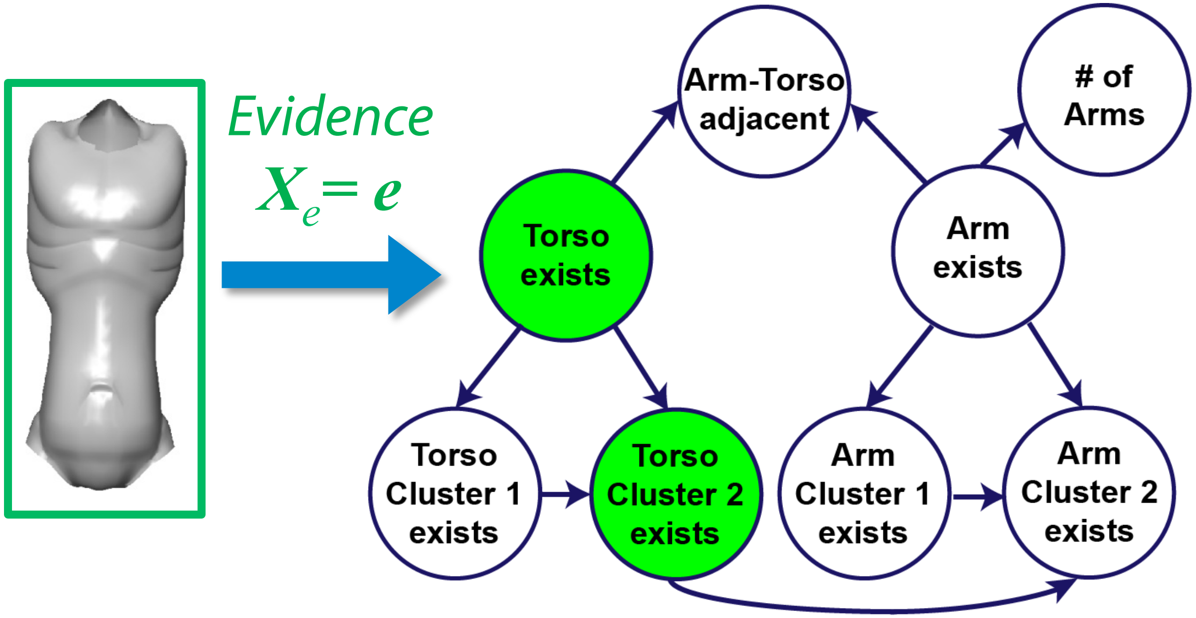
n: # of training shapes

Outline

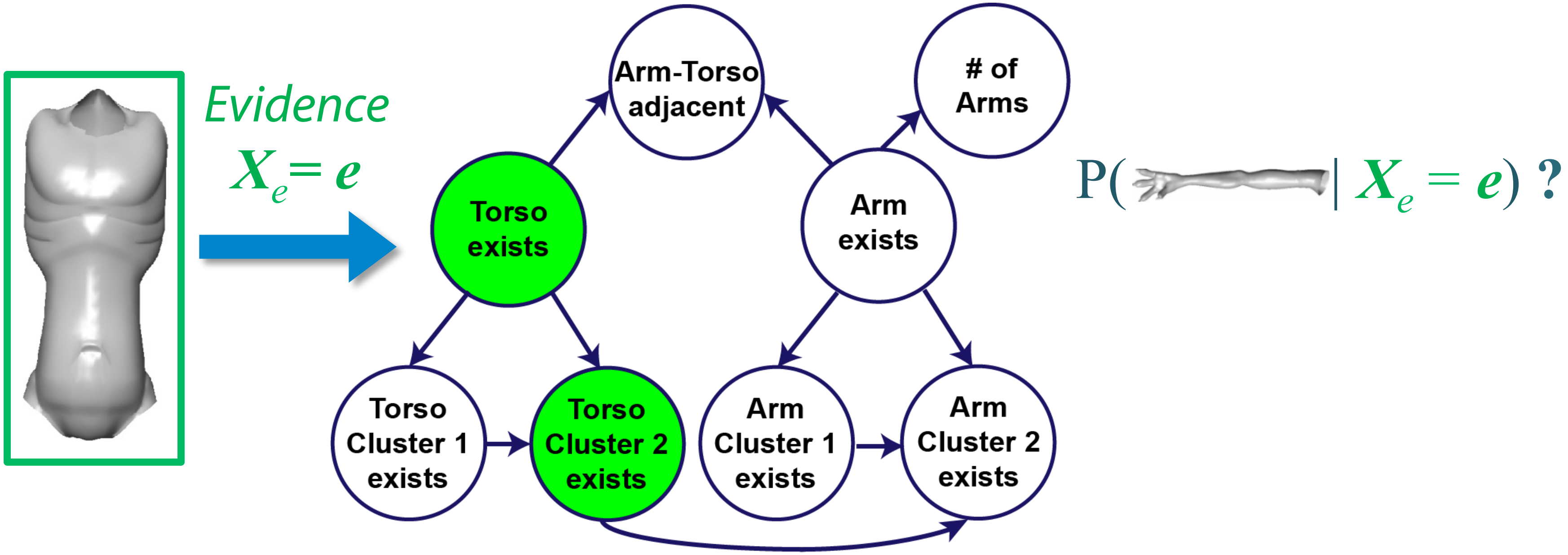
1. Probabilistic model definition
2. Learning
3. **Inference**
4. Results

Inference

Inference


Evidence
$X_e = e$
Arm-Torso adjacent
# of Arms
Torso exists
Arm exists
Torso Cluster 1 exists
Torso Cluster 2 exists
Arm Cluster 1 exists
Arm Cluster 2 exists

Inference


Evidence
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Torso exists
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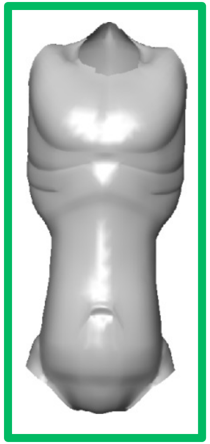
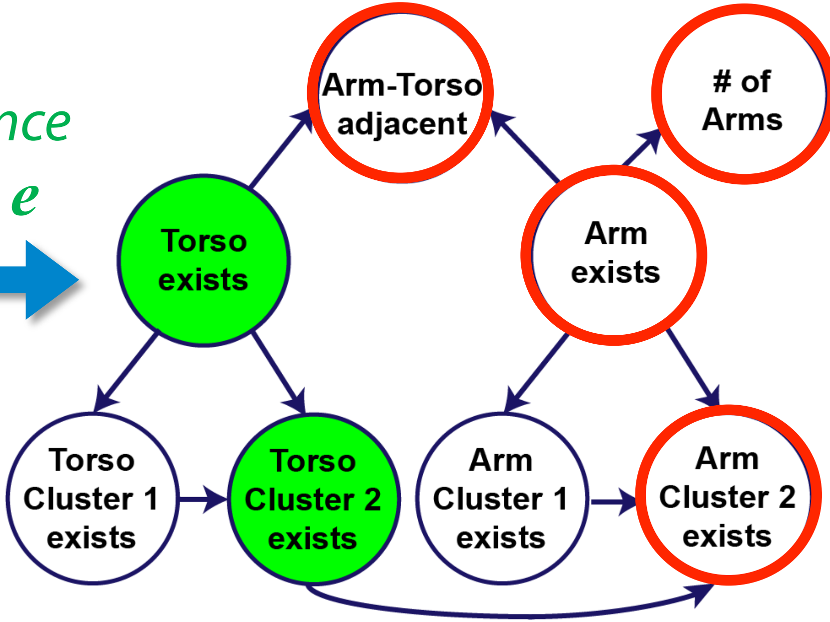
Arm Cluster 1 exists
Arm Cluster 2 exists
P(| $X_e = e$) ?

Inference



Evidence

$X_e = e$



$P(\ X_q = q \mid X_e = e\ )$

Particle-based inference

Outline

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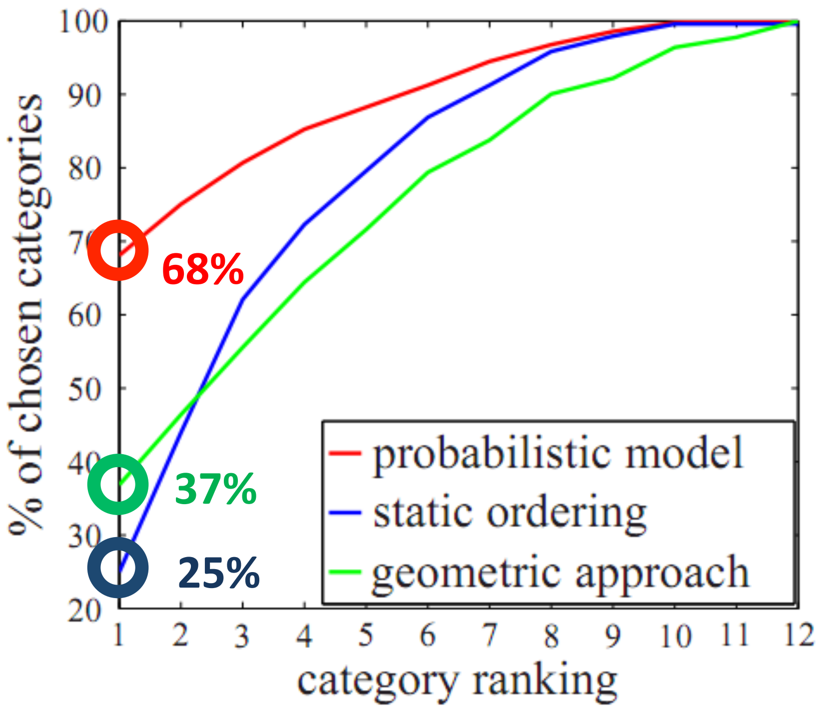
4. **Results**

Examples of shapes created by users

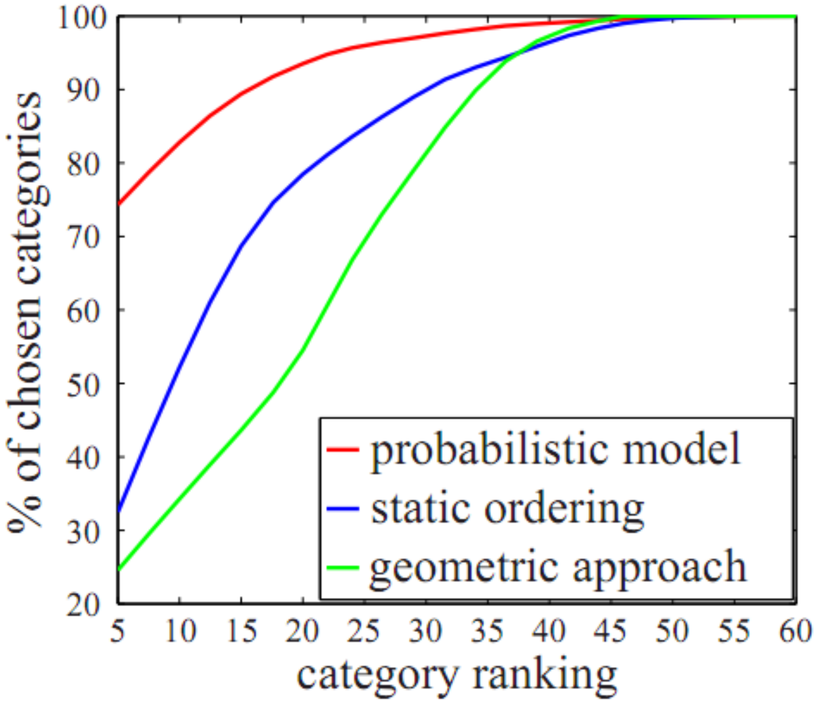
Evaluation

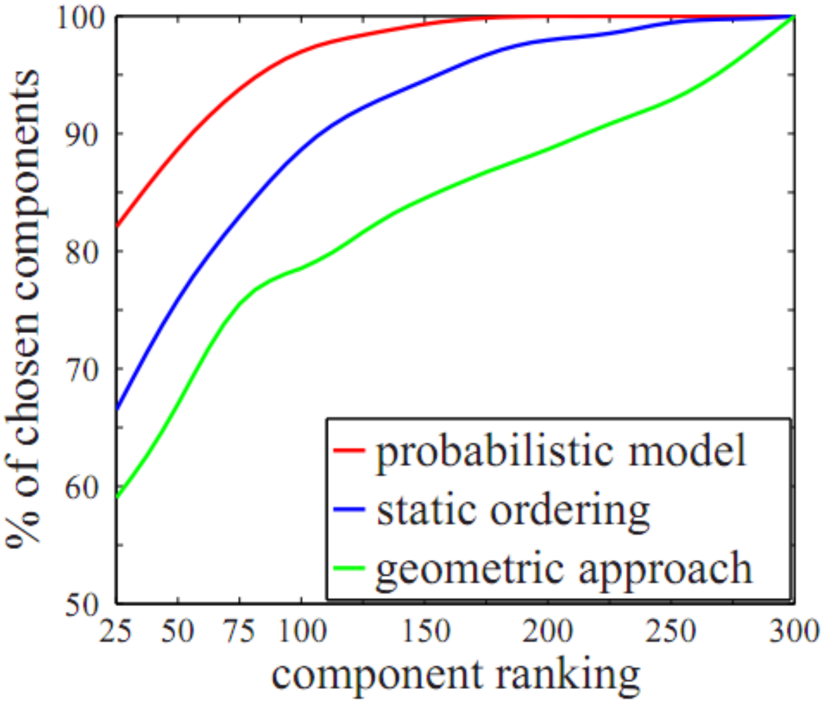
- 42 participants from the Stanford CS student body
- Each participant was asked to create 2 toys and 2 creatures
- Three conditions:
  - Dynamic ordering with probabilistic model
  - Static ordering of categories and components
  - Dynamic ordering with [Chaudhuri and Koltun 2010]

Relevance of suggested components – “Creatures” task

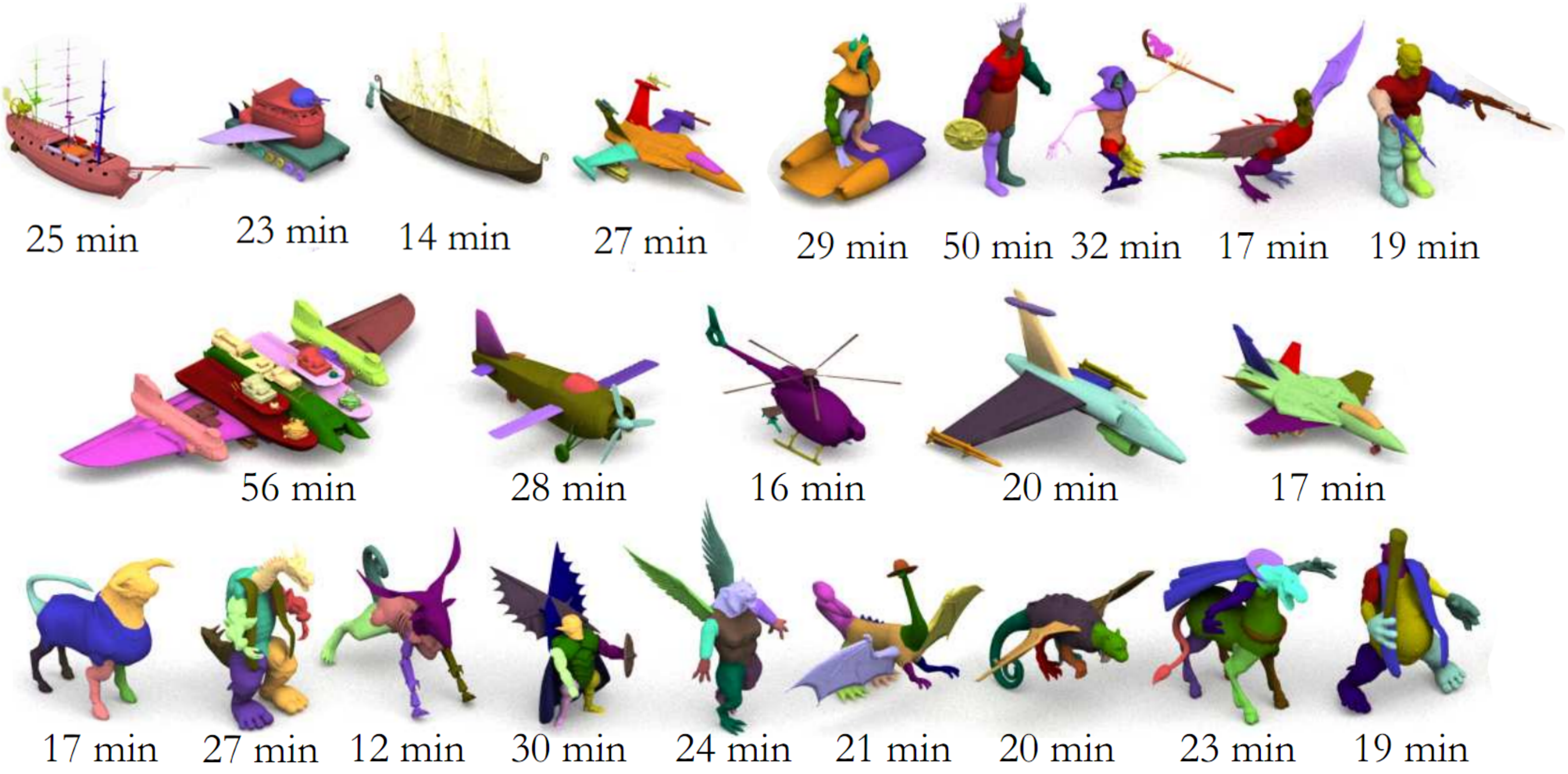


Relevance of suggested components – “Toy” task





Examples of shapes created by users



Summary

- Probabilistic reasoning for presenting components in assembly-based 3D modeling

- Probabilistic graphical model for encoding conditional dependencies between shape components

- Increases the relevance of suggested components

Future Work

- Better modeling of **stylistic**, **spatial** and **functional** relationships

- Benefits from advances in:
  - consistent shape **segmentation**
  - **gluing** and **cutting** components
  - **editing geometry** of individual components

Thank you!

Acknowledgements: **Aaron Hertzmann, Sergey Levine, Suchi Saria, Jonathan Laserson, Philipp Krähenbühl, Daphne Koller, Chris Platz, Hadidjah Chamberlin, Niels Joubert**

Our project web page:

http://graphics.stanford.edu/~sidch/projects/assembly/

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BACKUP/OTHER SLIDES

Gaussian mixture model for style clustering

Component features:

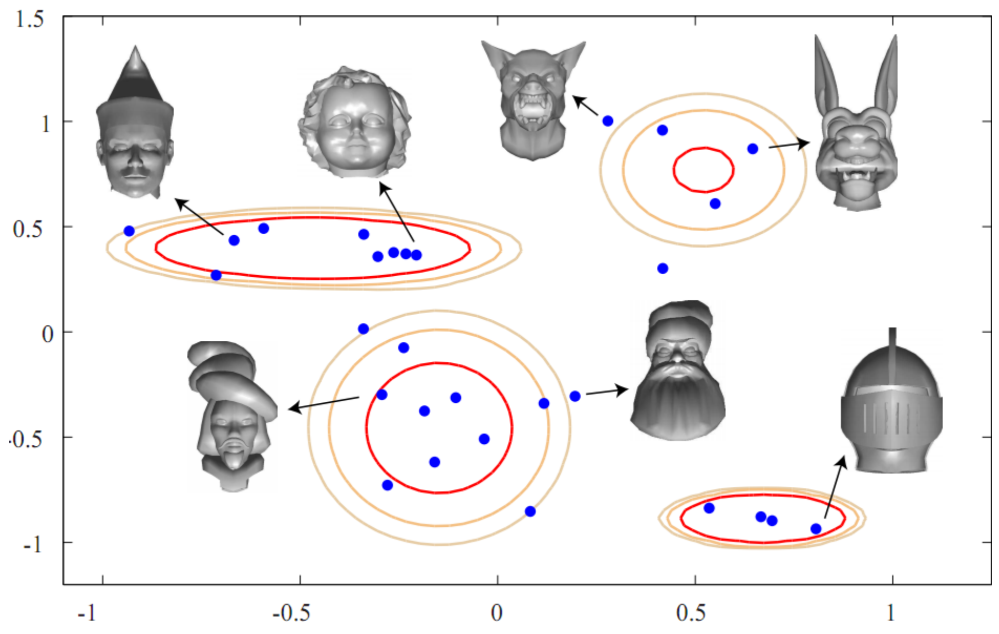
Shape diameter

Curvature

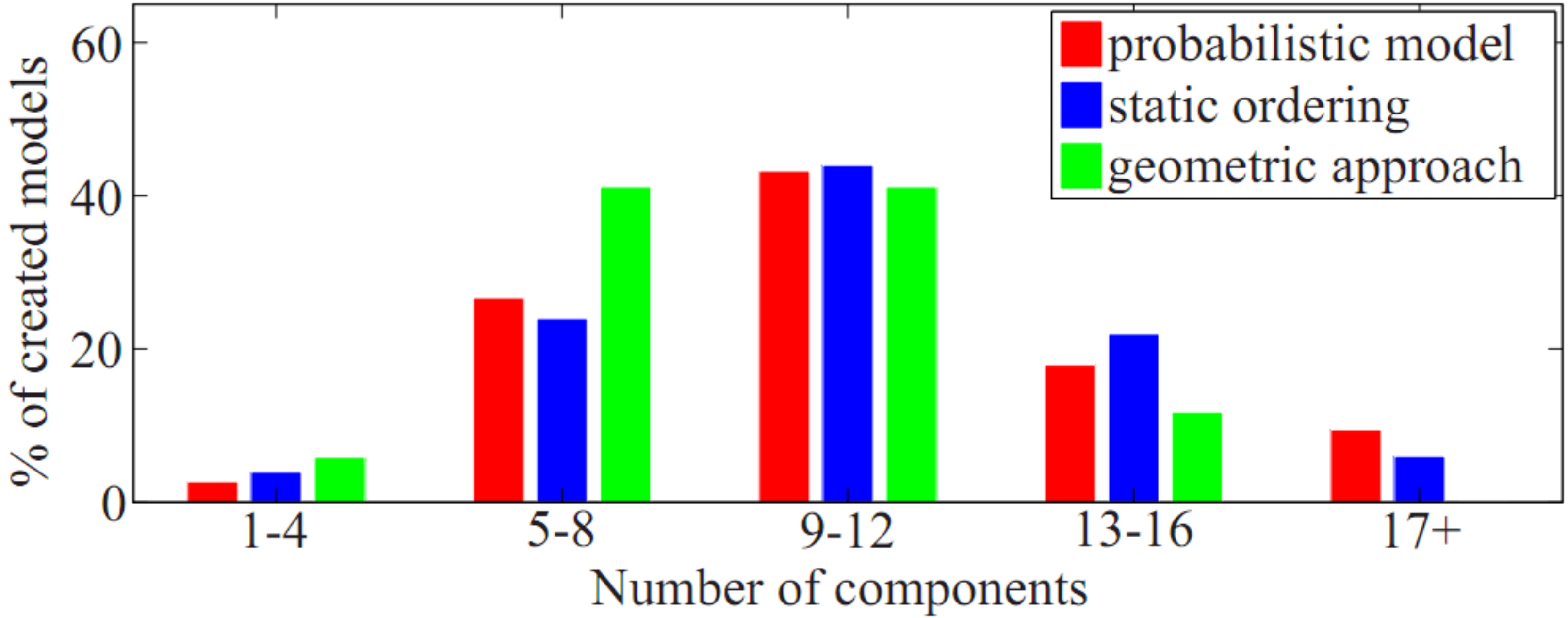
Singular values from PCA

Average geodesic distance

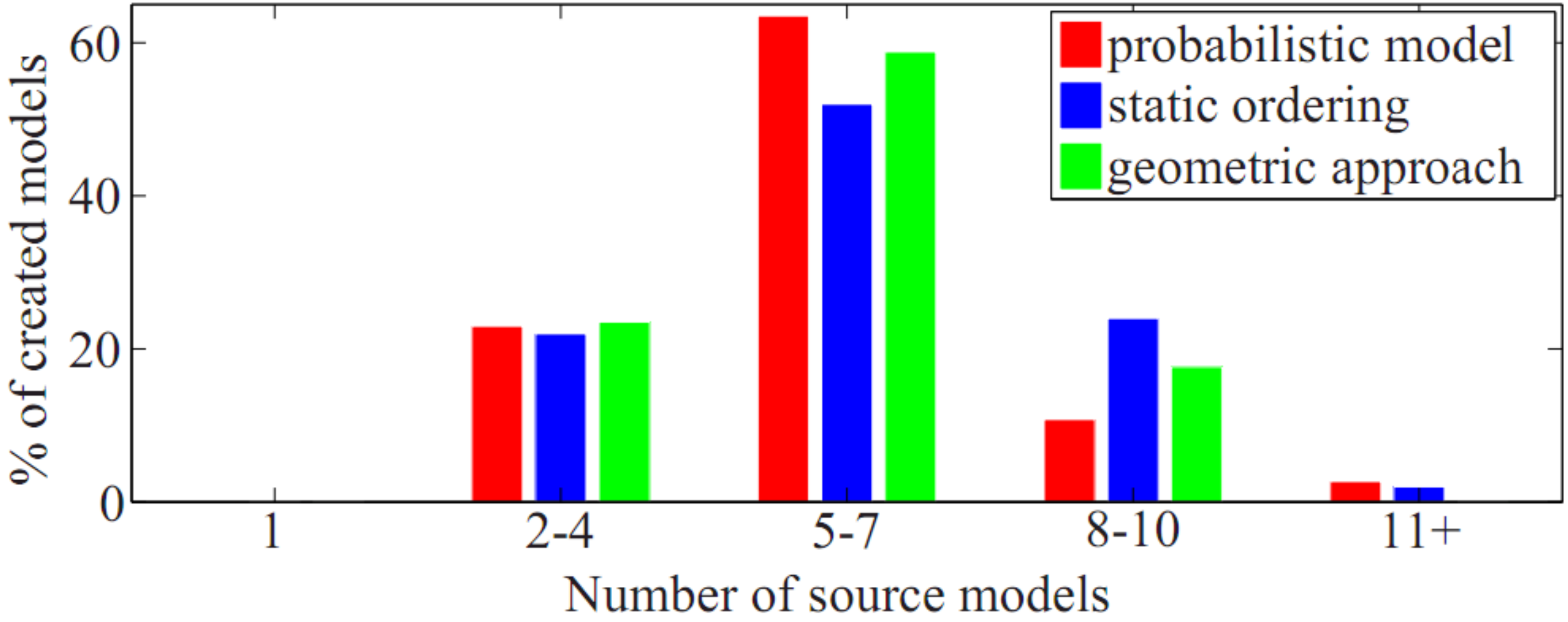
Geodesic distance from other components



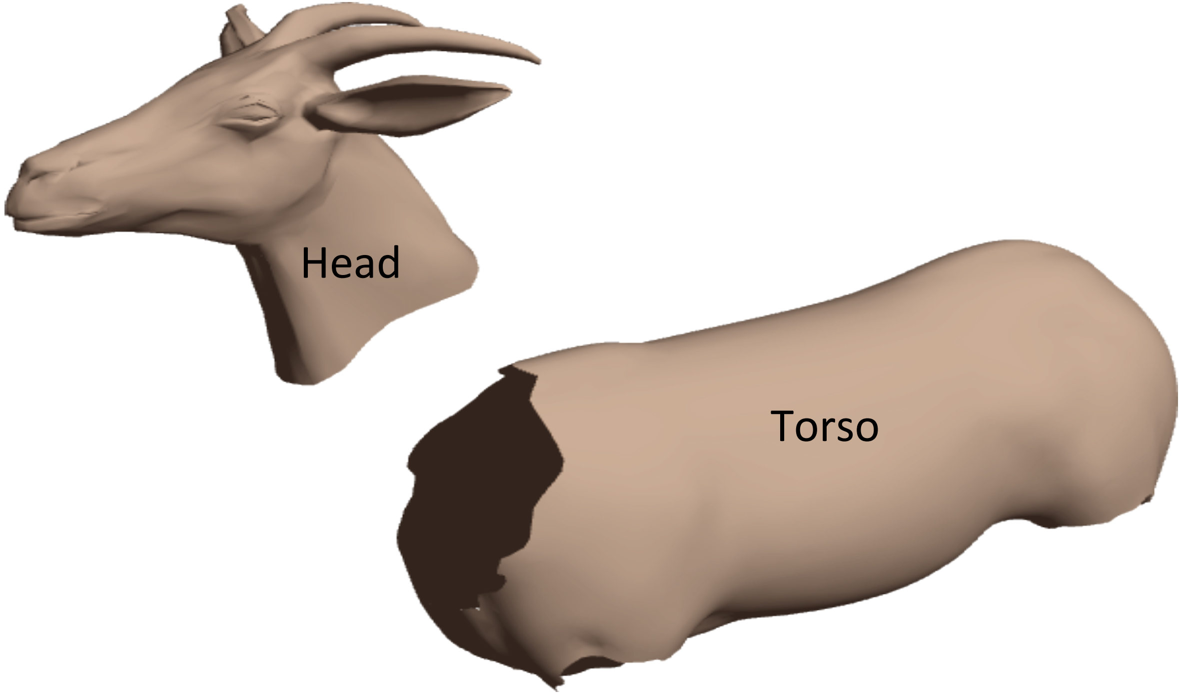
Number of components used per shape



Number of source models contributing to each shape



Component Assembly



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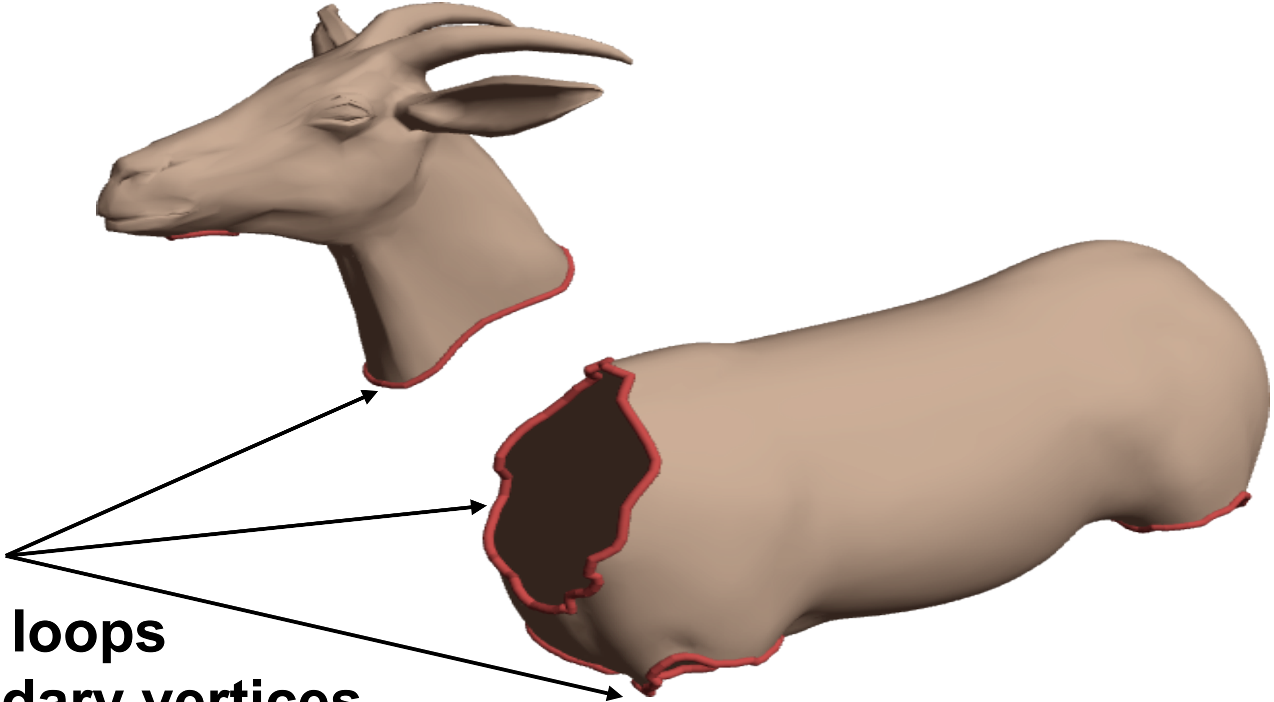
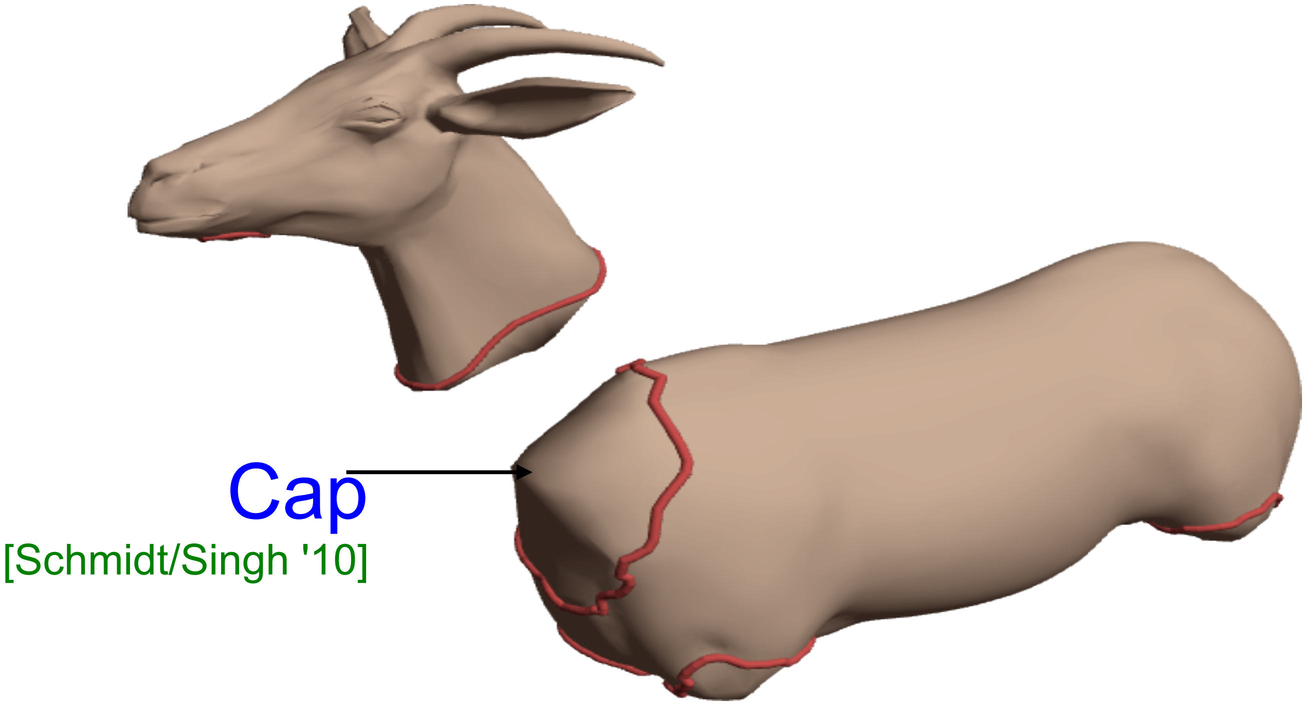
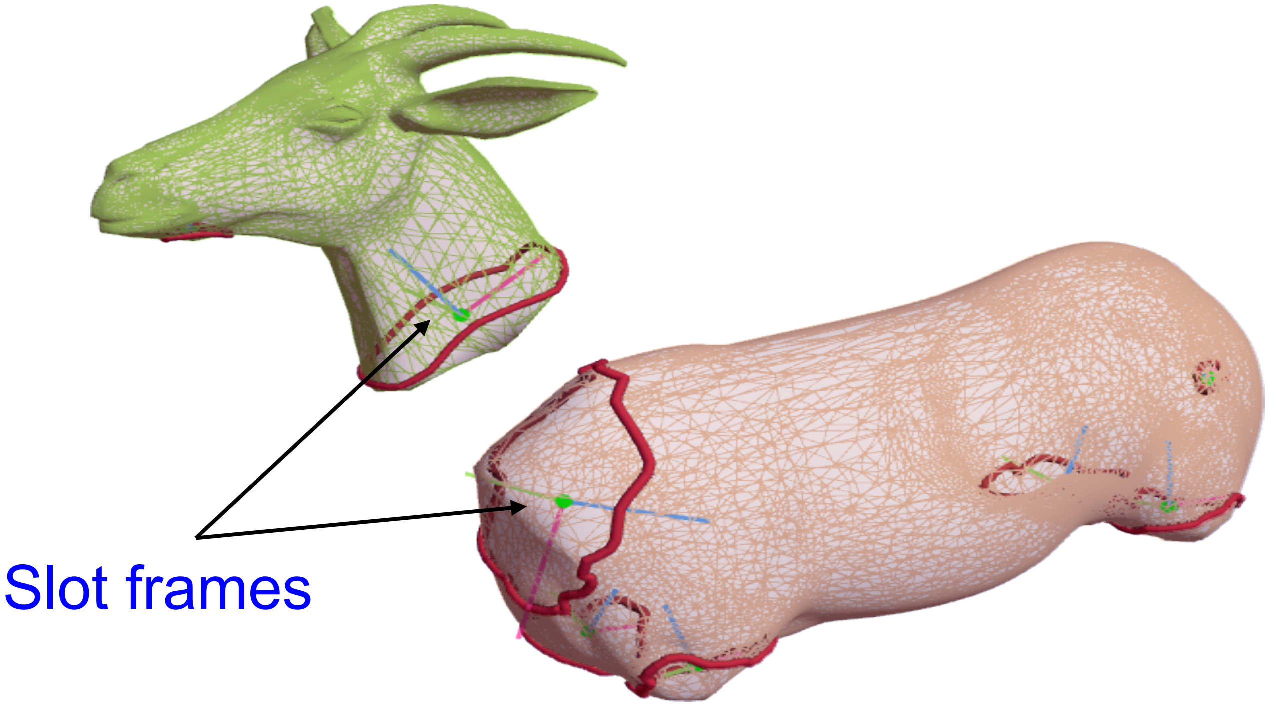


Slots
Edge loops
Boundary vertices
Zones

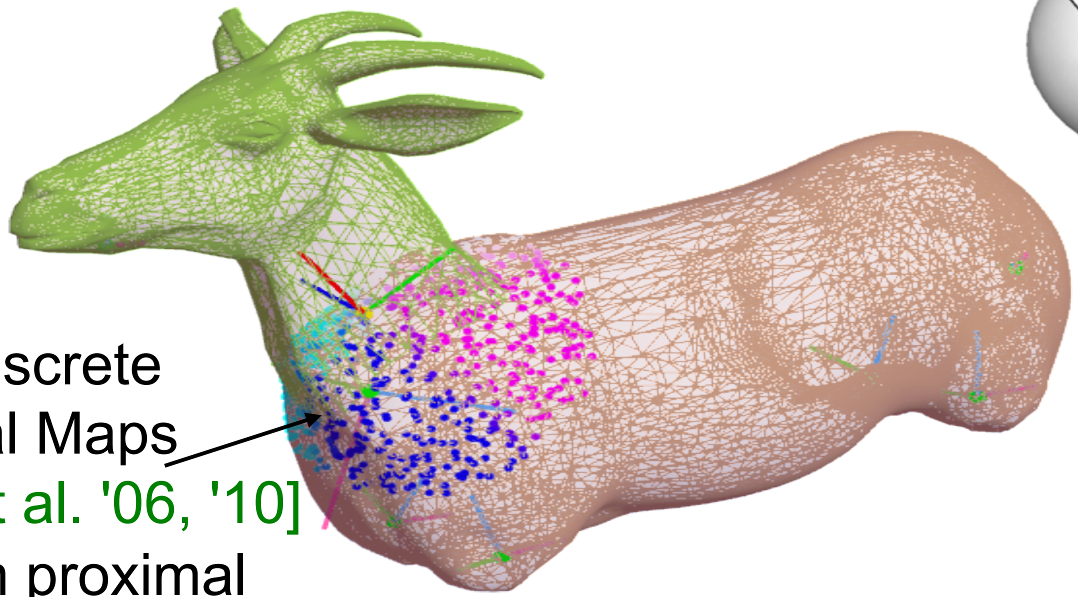
Component Assembly

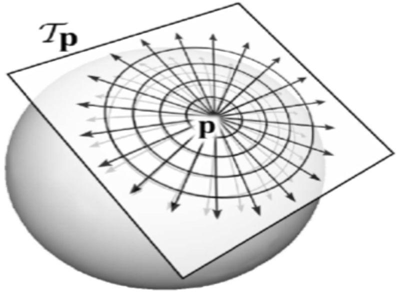


Component Assembly



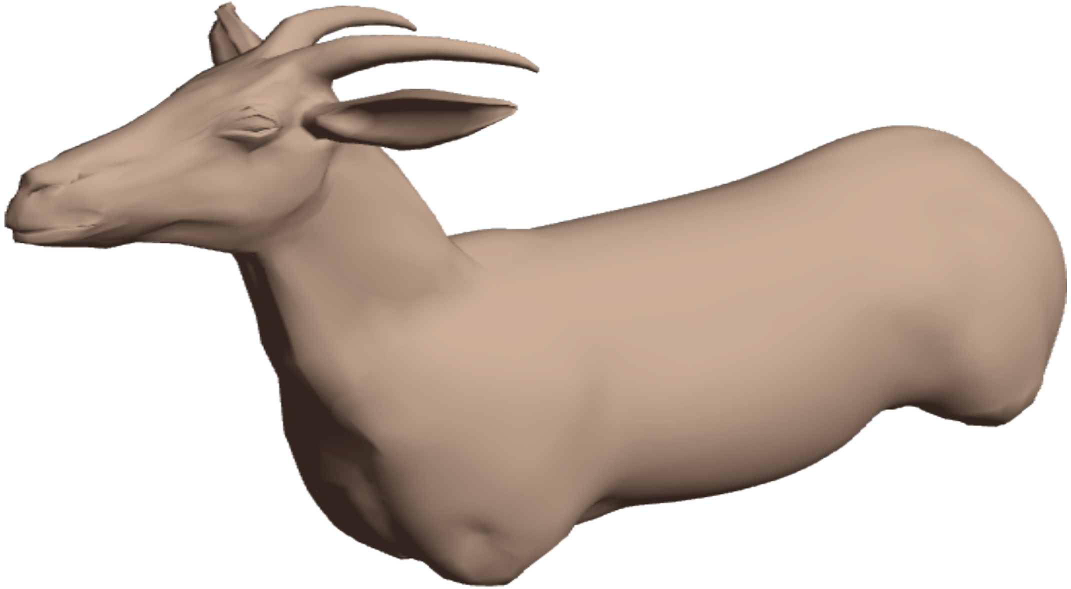
Component Assembly



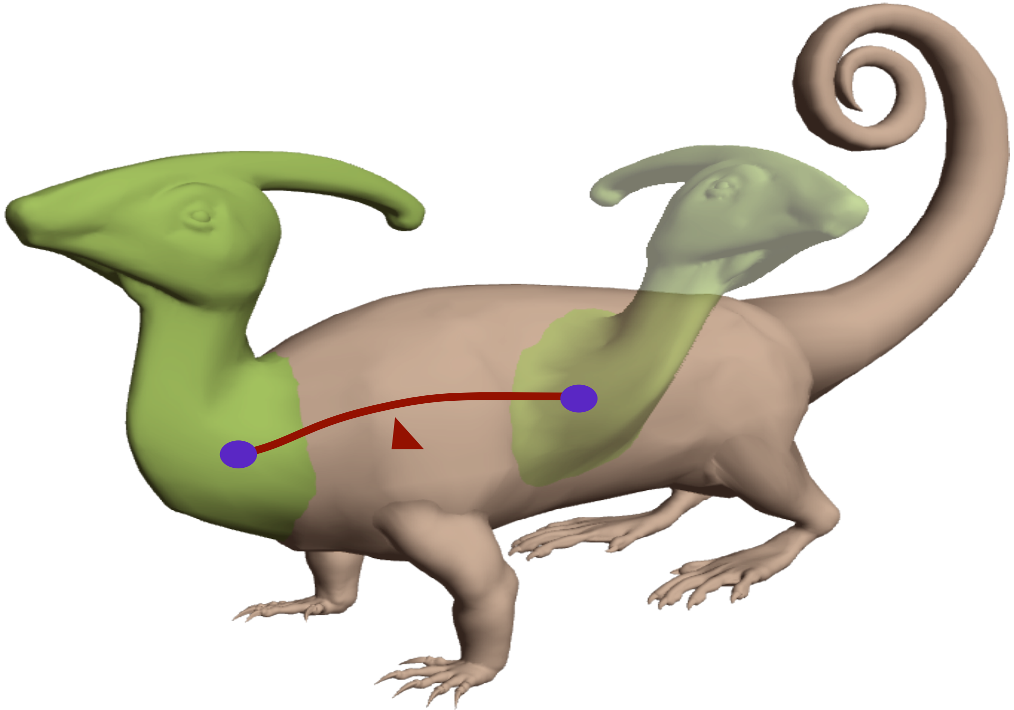


Register Discrete
Exponential Maps
[Schmidt et al. '06, '10]
and deform proximal
regions for smooth join
(note: gluing is asymmetric, *not* slot-to-slot)

Component Assembly

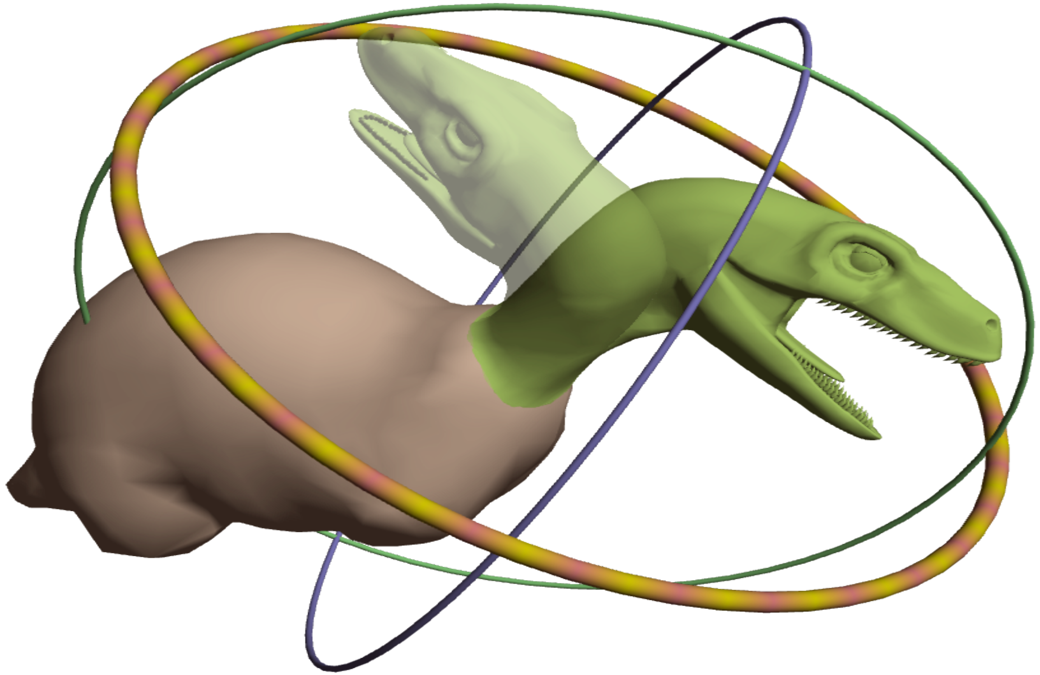


Constrained Translation



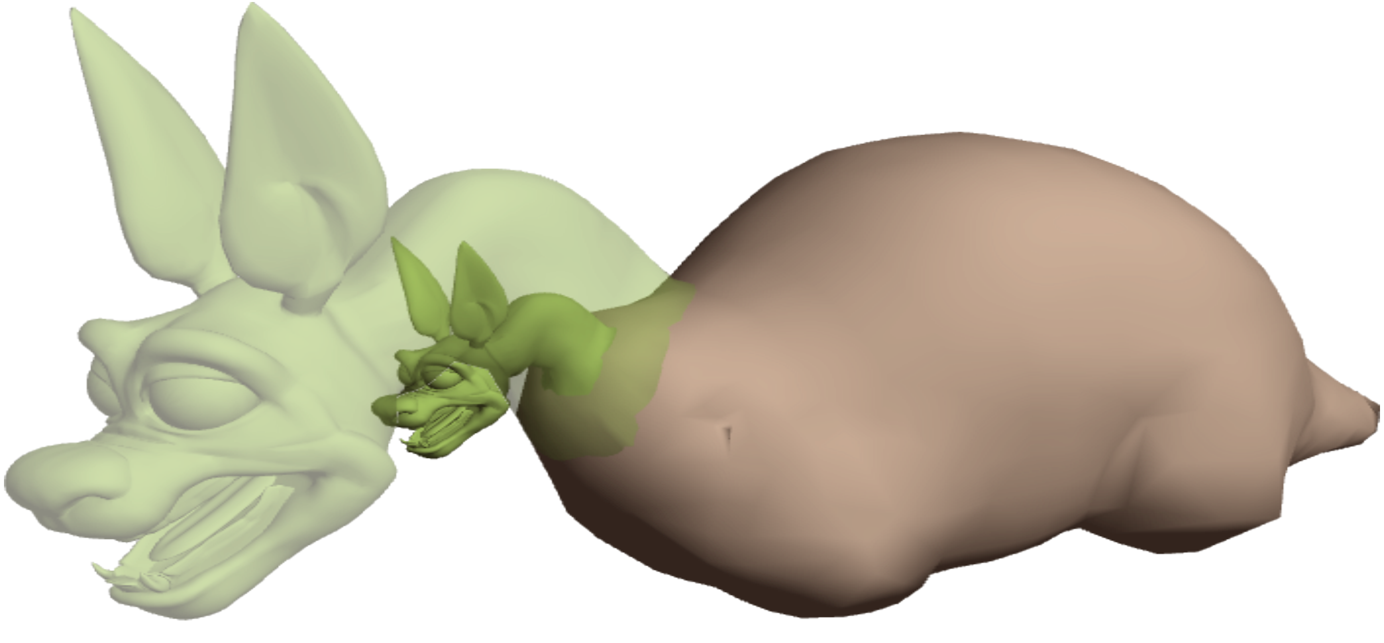
Incremental tangential motion following mouse drag
“Steps over” small surface detail

Constrained Rotation



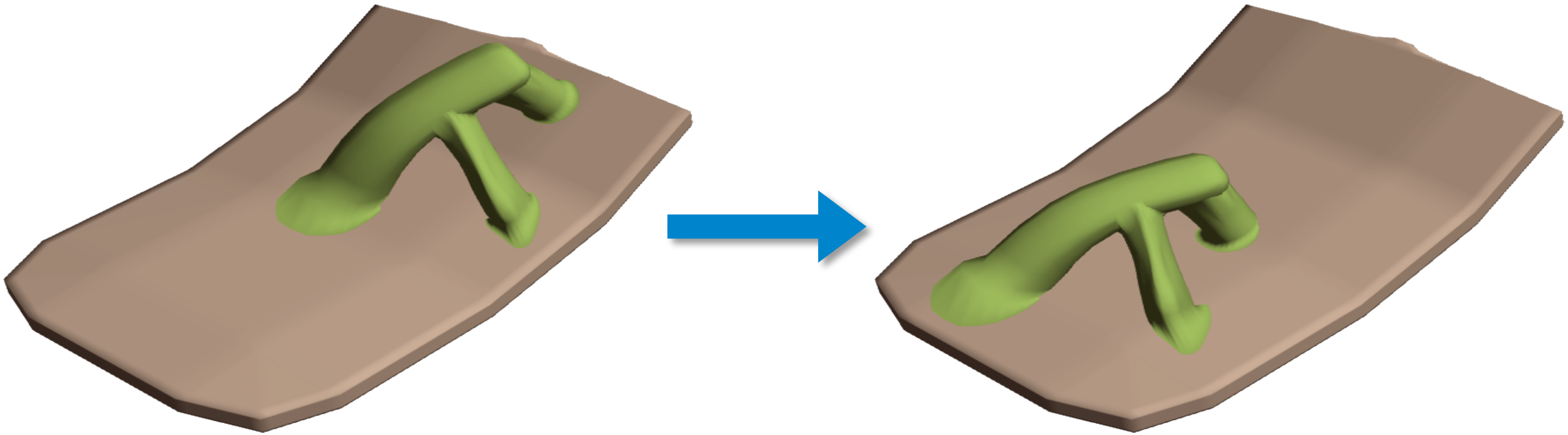
1-DOF rotation in plane of attachment (selected above)
2-DOF rotation for tilt

Constrained Scaling



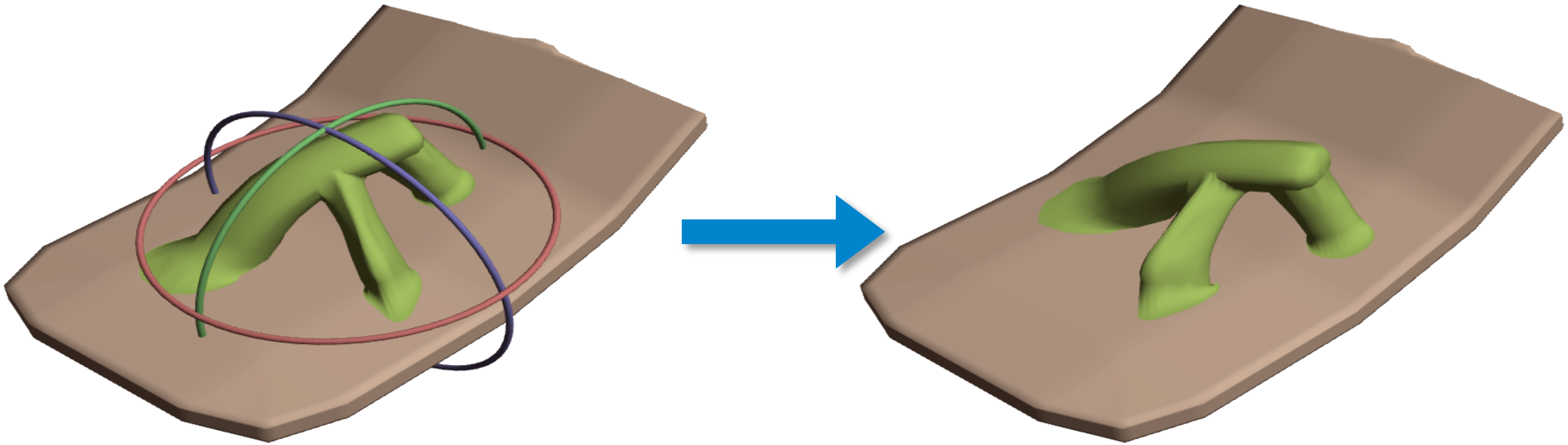
Maintain point(s) of attachment

Multiple Constraints



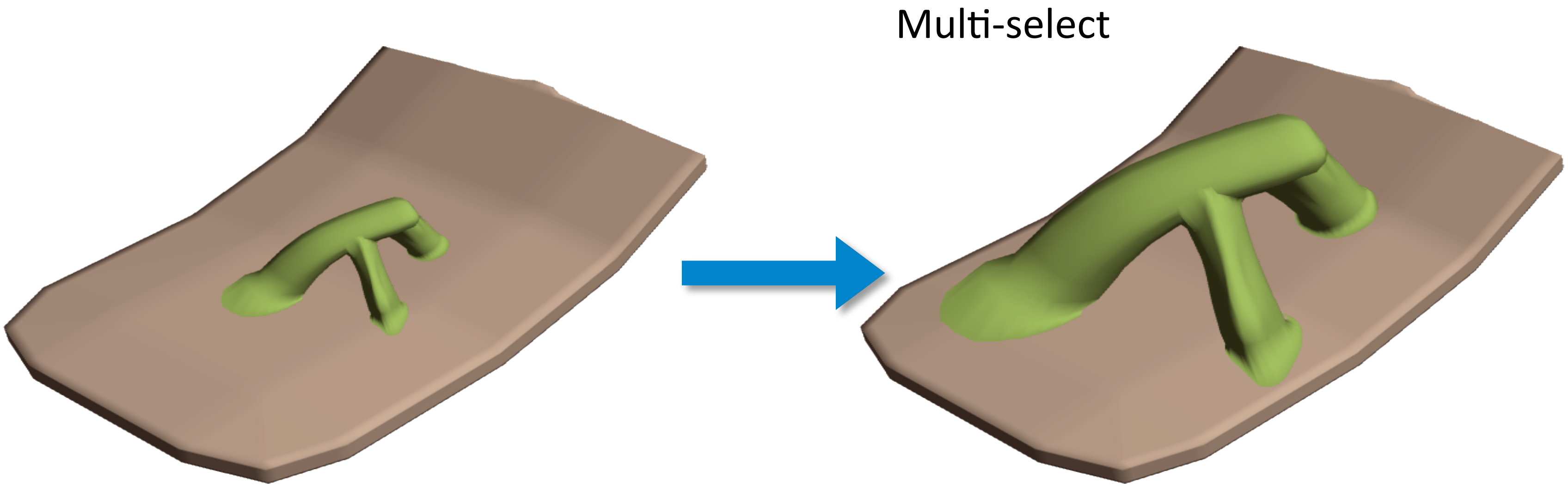
Slide each attached slot individually
Overall motion computed from slot displacements
Motion prevented if not possible without breaking attachments

Multiple Constraints



Rotation axis computed from all current attachments
Rotation prevented if not possible without breaking attachments

Multiple Constraints

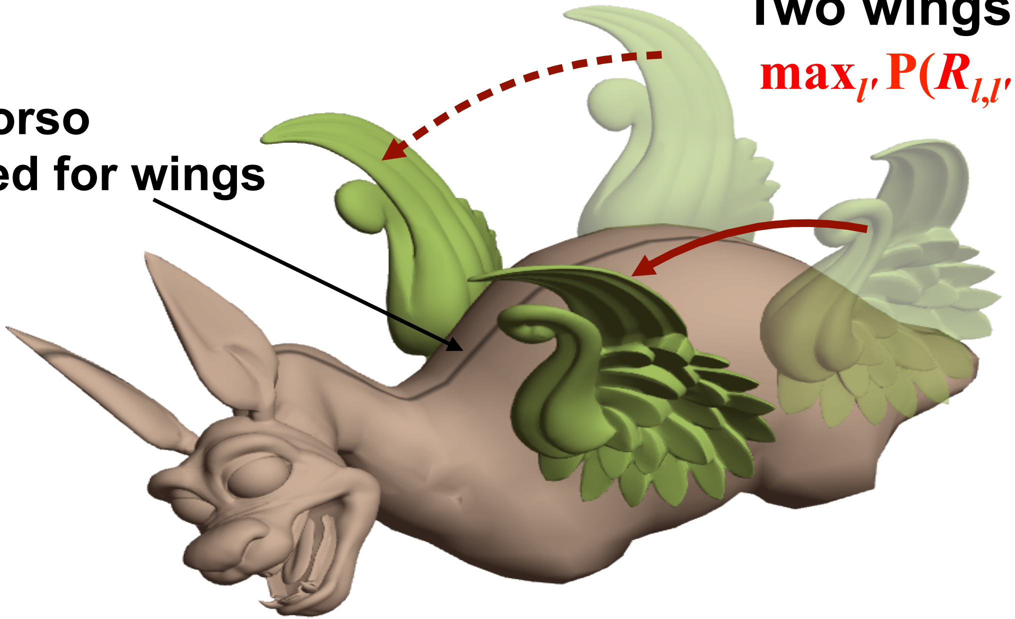


Scaling pivot computed from all current attachments
Scaling prevented if not possible without breaking attachments

Symmetry

Two wings created, since
$\max_{l'} P(R_{l,l'} \mid e) > 0$

Symmetry plane of torso automatically selected for wings



Query Bayesian Network for $\arg\max_{l'} P(R_{l,l'} \mid e)$

l **is label of selected part,** l' **is label of another part in the assembly**

Initial Adjacency

Legs snap to torso...

… but horns snap to head

Query Bayesian Network for $\arg\max_{l'} P(A_{l,l'} \mid e)$

l **is label of selected part,** l' **is label of another part in the assembly**

Modeling Interface

Modeling Area