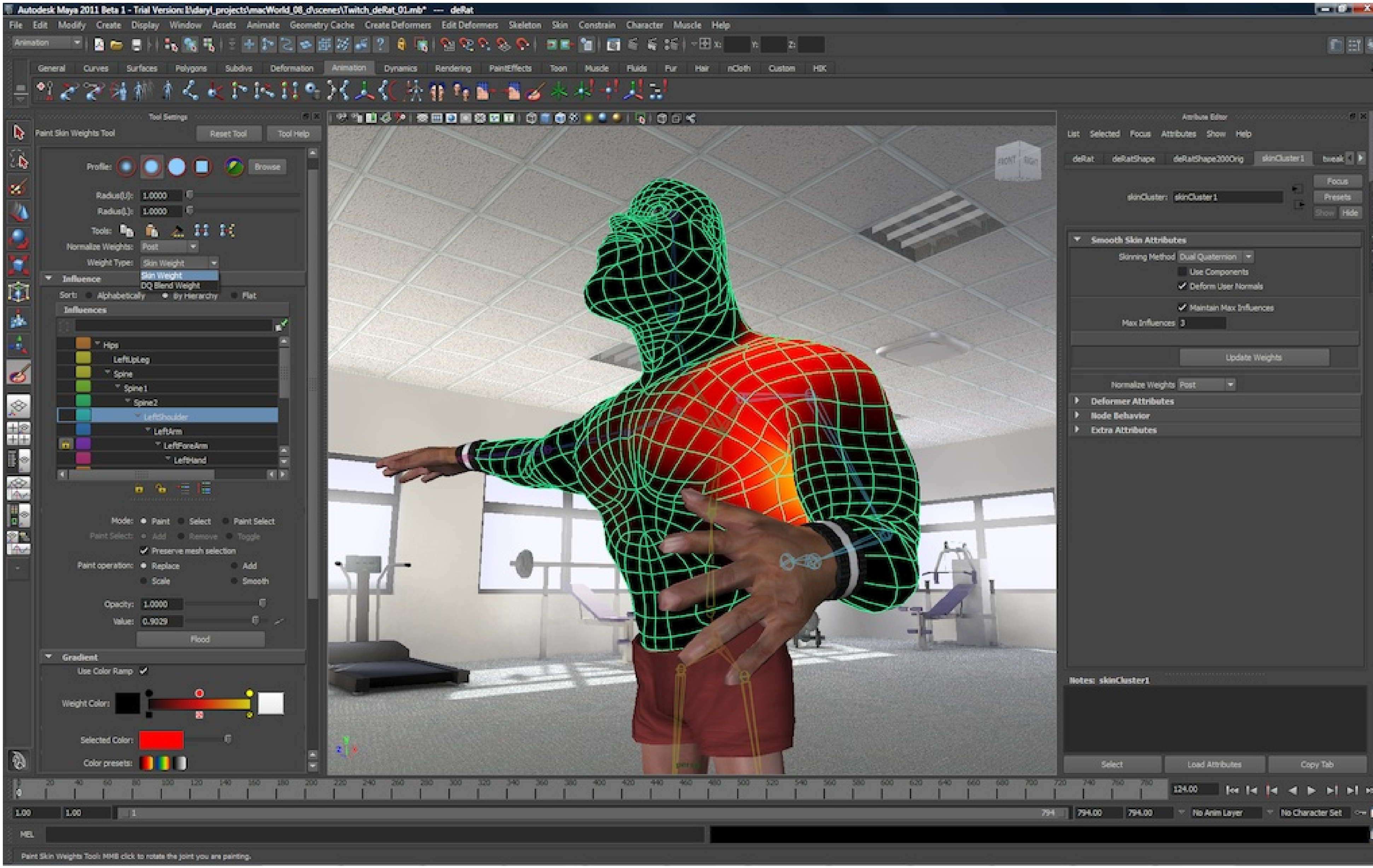
Data-Driven Design

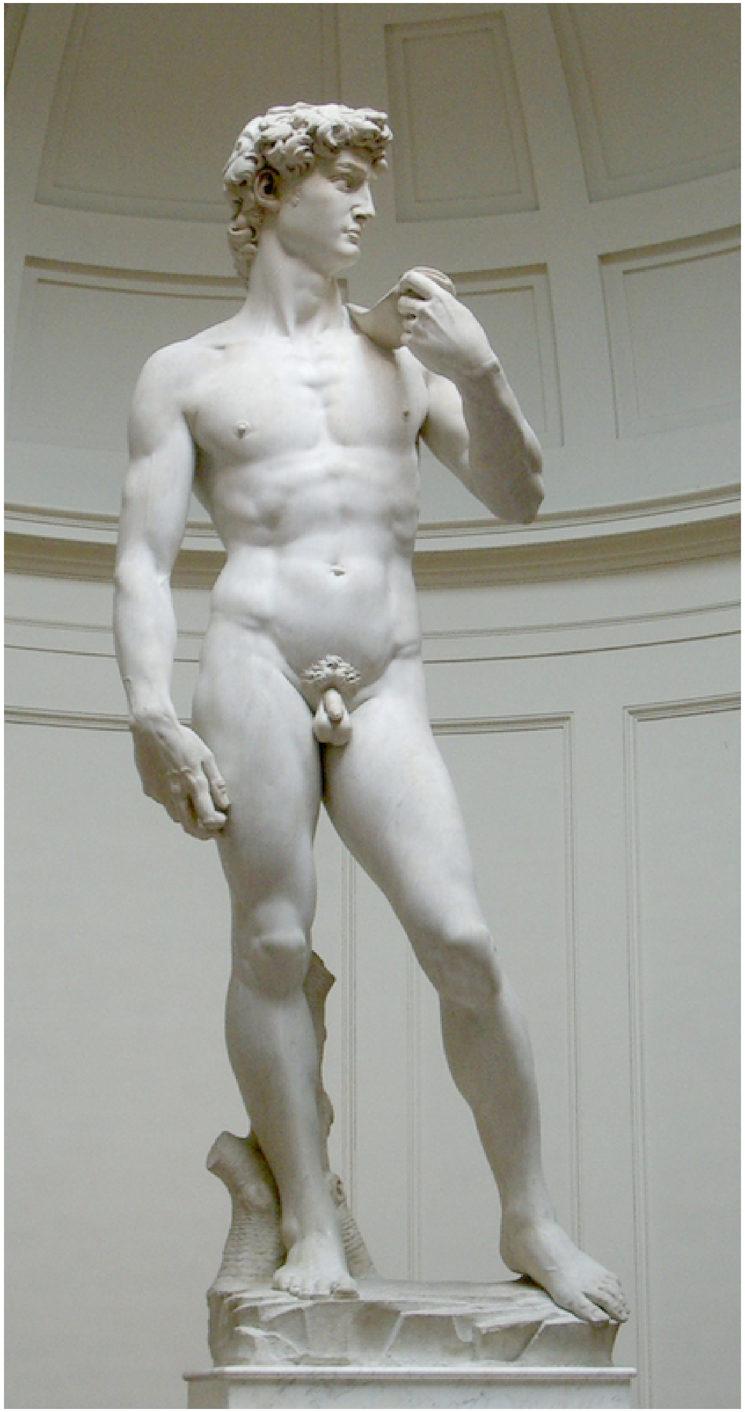
Siddhartha Chaudhuri

CS749: Digital Geometry Processing
Spring 2016

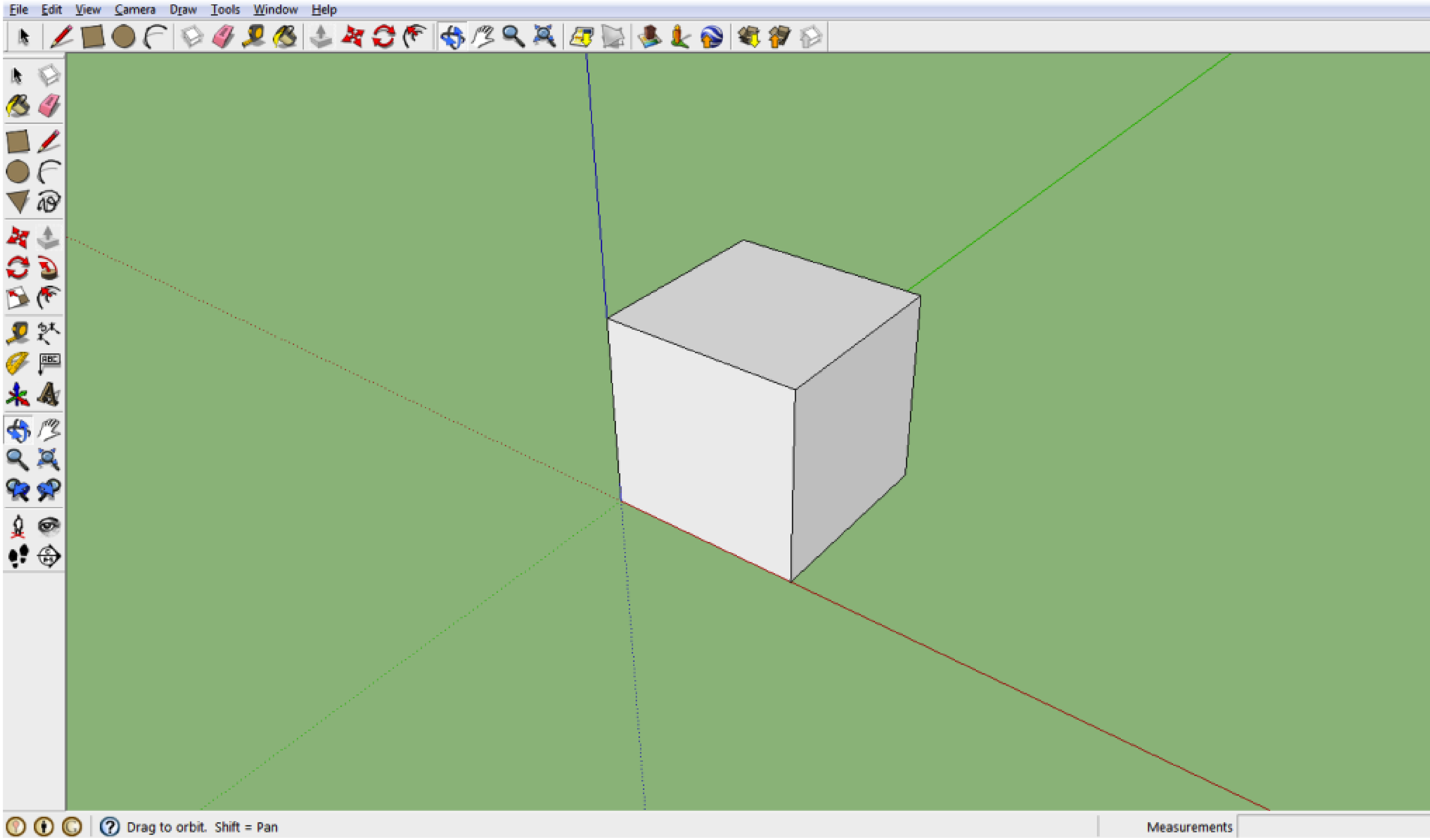
http://www.cse.iitb.ac.in/~cs749



Autodesk, Inc.



silmaril@wikipedia


File Edit View Camera Draw Tools Window Help
Drag to orbit. Shift = Pan
Measurements

rollins.edu

How can we create more widely usable design tools?

- Humans give high-level directions
- Computers handle low-level details

Design as Optimization

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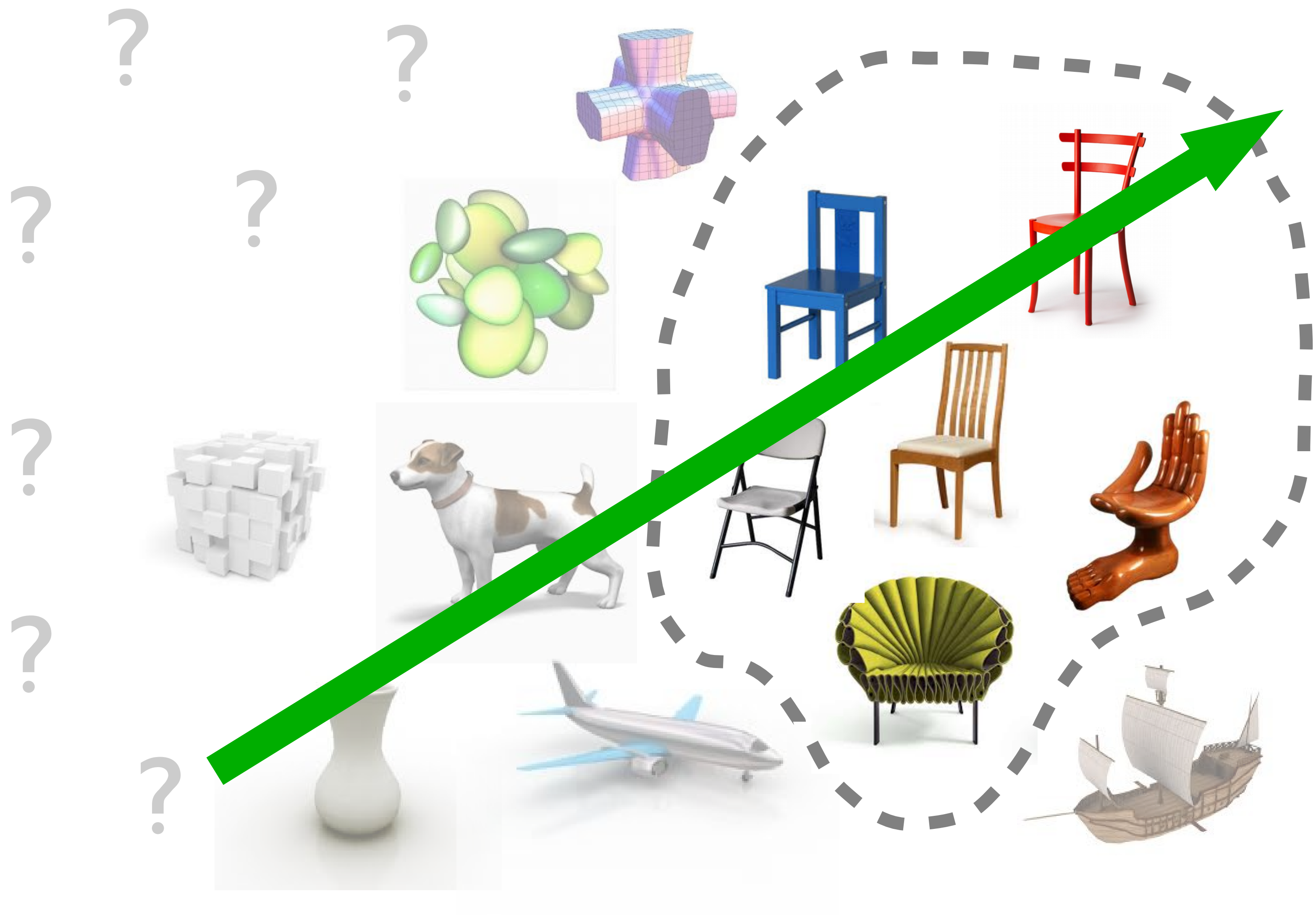
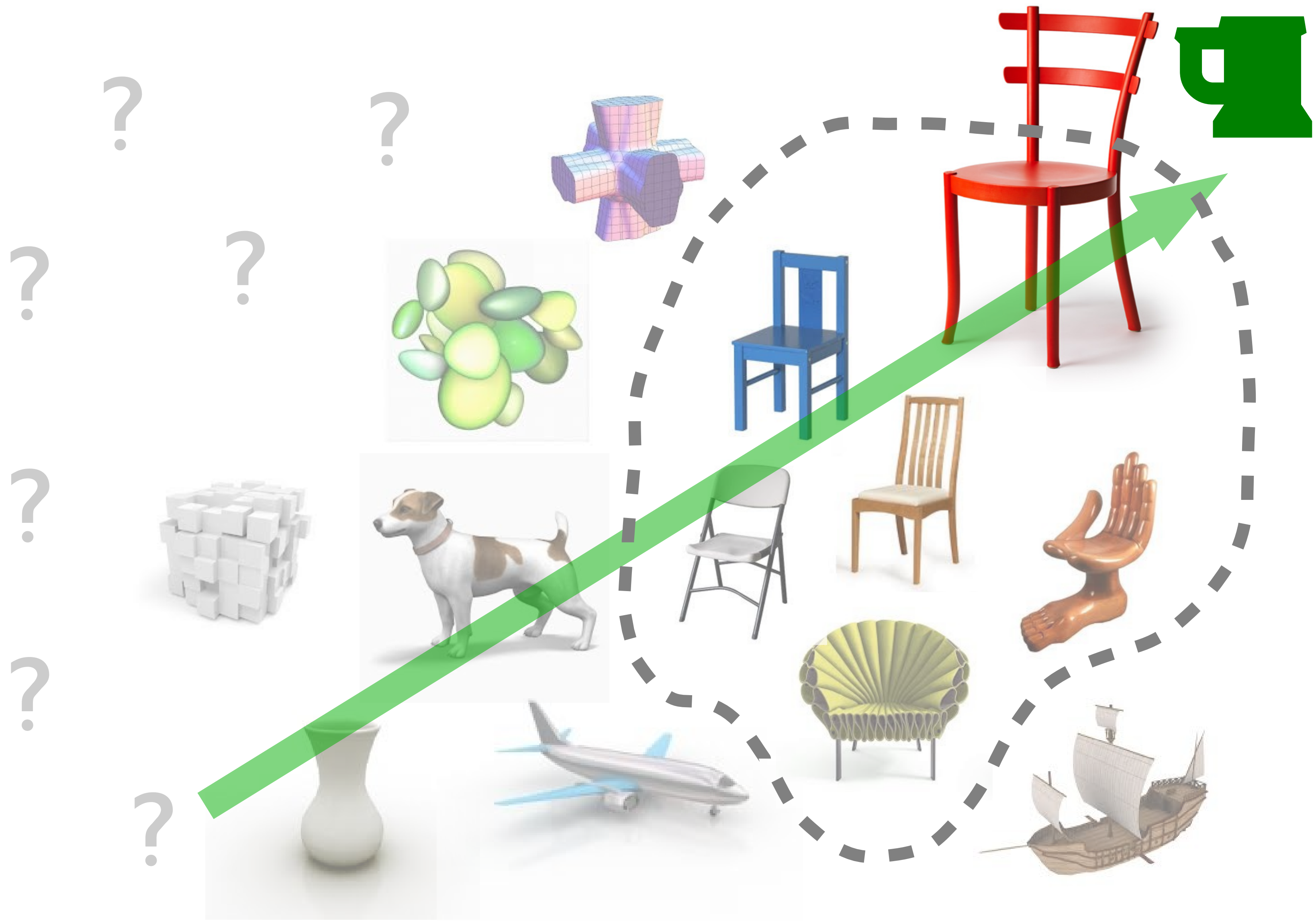


Design as Optimization



2 Big Questions

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- How can we identify the **feasible** regions of design space?

  (Optimization *constraint*)

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  (Optimization *constraint*)

- How can people specify design **intent**?

  (Optimization *objective*)

Outline

- Learning design structure from repositories of shapes
  - **Probabilistic models** of shape

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  - Semantic **attributes** (*scary, artistic,* ...)
  - Mechanical **function** (*this airplane should fly*...)
  - Human **interaction** (*sit comfortably in a chair*...)

What is the role of data?

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- **Reuse** (of existing components)

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- **Training** (of computational models)

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- **Reuse** (of existing components)
- **Training** (of computational models)
- **Inspiration** (for new designs)

Outline

- Learning design structure from repositories of shapes
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- Learning to capture design intent
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- **General**
    - Topological/geometric/configurational variety

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  - Topological/geometric/configurational variety
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  - Some designs are more plausible than others
- **Generative**
  - Can be used to produce new designs
- **Meaningfully Parametrized**
  - Design intent readily maps to “suitable” designs

Design Space: Maya

Sequences of commands to Maya/AutoCAD/ZBrush...

Generality: **High**

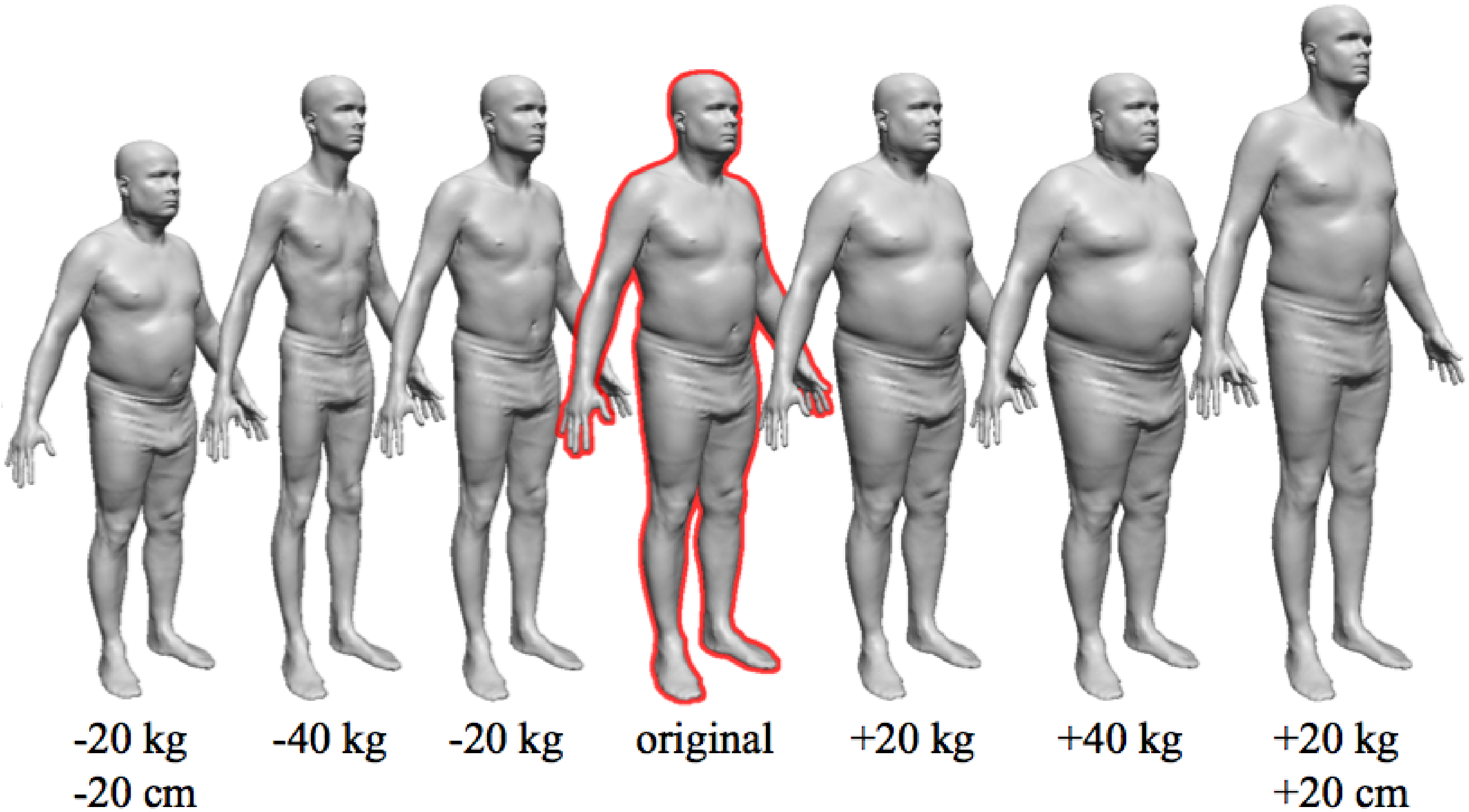
Probabilistic: **No**

Meaningful parametrization: **No**

Data-driven: **No**

Design Space: Deformable Template

(one topology, plus parameters for body type)



Generality: **Low**

Probabilistic: **Yes**

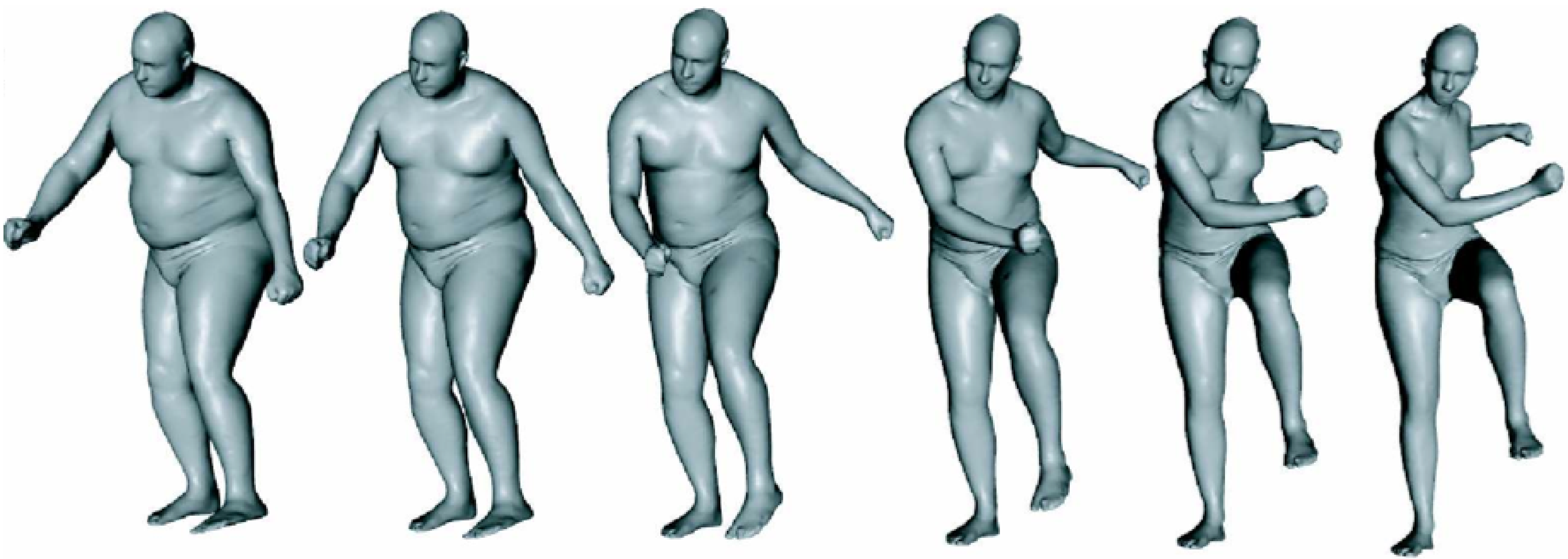
Meaningful parametrization: **Moderate**

Data-driven: **Yes**

Allen, Curless and Popovic, 2003

Design Space: Deformable Template

(one topology, plus parameters for both body type and pose)

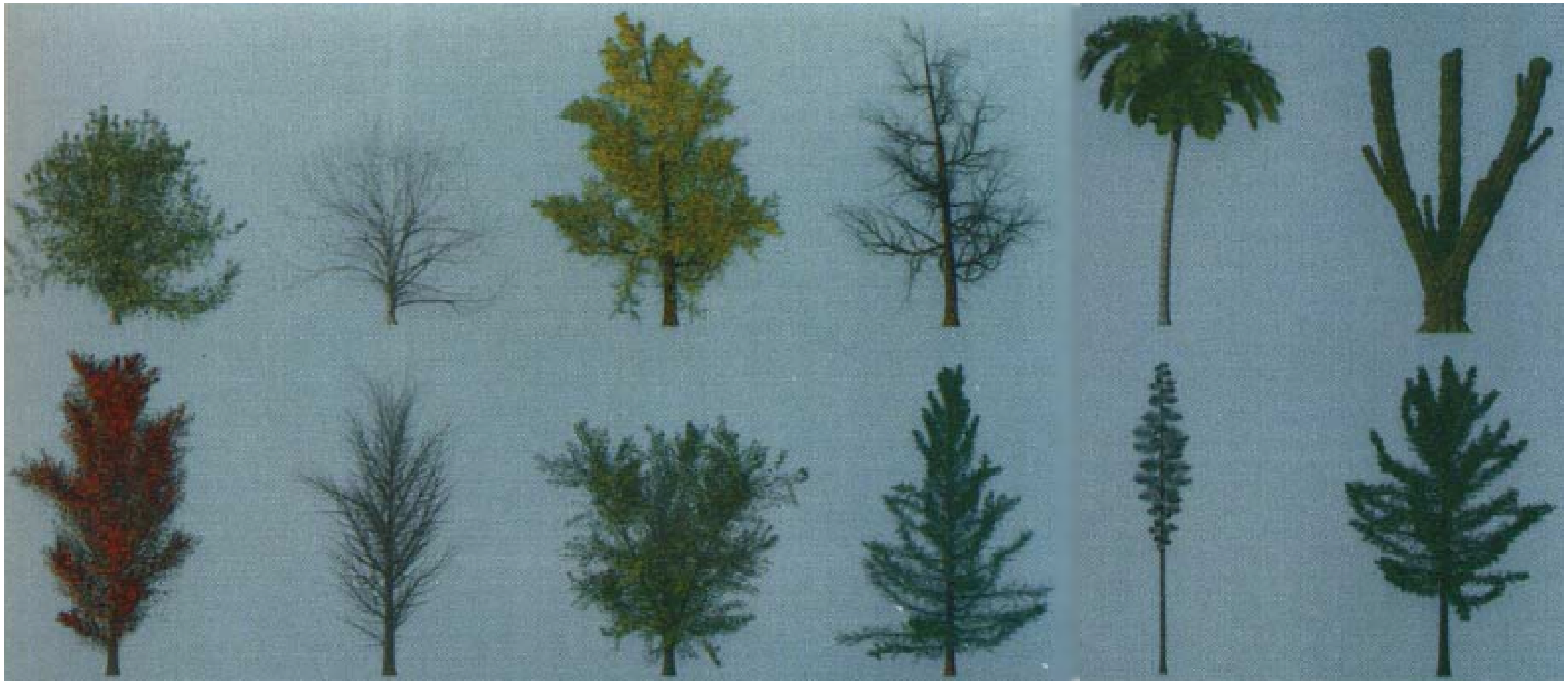


Generality:	**Low-ish**	Meaningful parametrization:	**Moderate**
Probabilistic:	**Yes**	Data-driven:	**Yes**

Anguelov et al., 2005

Design Space: Parametrized Procedure

(fixed set of parameters)



Generality: **Moderate** Meaningful parametrization: **Yes**

Probabilistic: **No** Data-driven: **No**

Weber and Penn, 1995

Design Space: Probabilistic Procedure

(probability distribution on parameters)

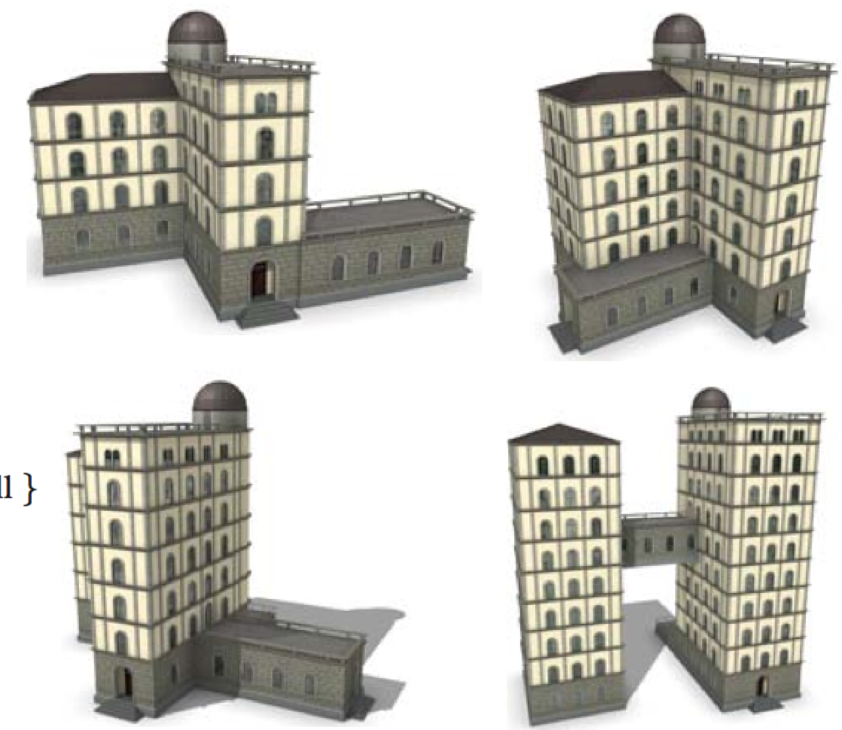
Generality:	Moderate	Meaningful parametrization:	Yes
Probabilistic:	Yes	Data-driven:	Partially

Talton et al., 2009

Design Space: Probabilistic Grammar

(hierarchical generation)

```
PRIORITY 1:
1:  footprint ⇝ S(1r,building_height,1r) facades
      T(0,building_height,0) Roof("hipped",roof_angle){ roof }
PRIORITY 2:
2:  facades ⇝ Comp("sidefaces"){ facade }
3:  facade : Shape.visible("street")
      ⇝ Subdiv("X",1r,door_width*1.5){ tiles | entrance } : 0.5
      ⇝ Subdiv("X",door_width*1.5,1r){ entrance | tiles } : 0.5
4:  facade ⇝ tiles
5:  tiles ⇝ Repeat("X",window_spacing){ tile }
6:  tile ⇝ Subdiv("X",1r,window_width,1r){ wall |
      Subdiv("Y",2r,window_height,1r){ wall | window | wall } | wall }
7:  window : Scope.occ("noparent") != "none" ⇝ wall
8:  window ⇝ S(1r,1r,window_depth) I("win.obj")
9:  entrance ⇝ Subdiv("X",1r,door_width,1r){ wall |
      Subdiv("Y",door_height,1r){ door | wall } | wall }
10: door ⇝ S(1r,1r,door_depth) I("door.obj")
11: wall ⇝ I("wall.obj")
```



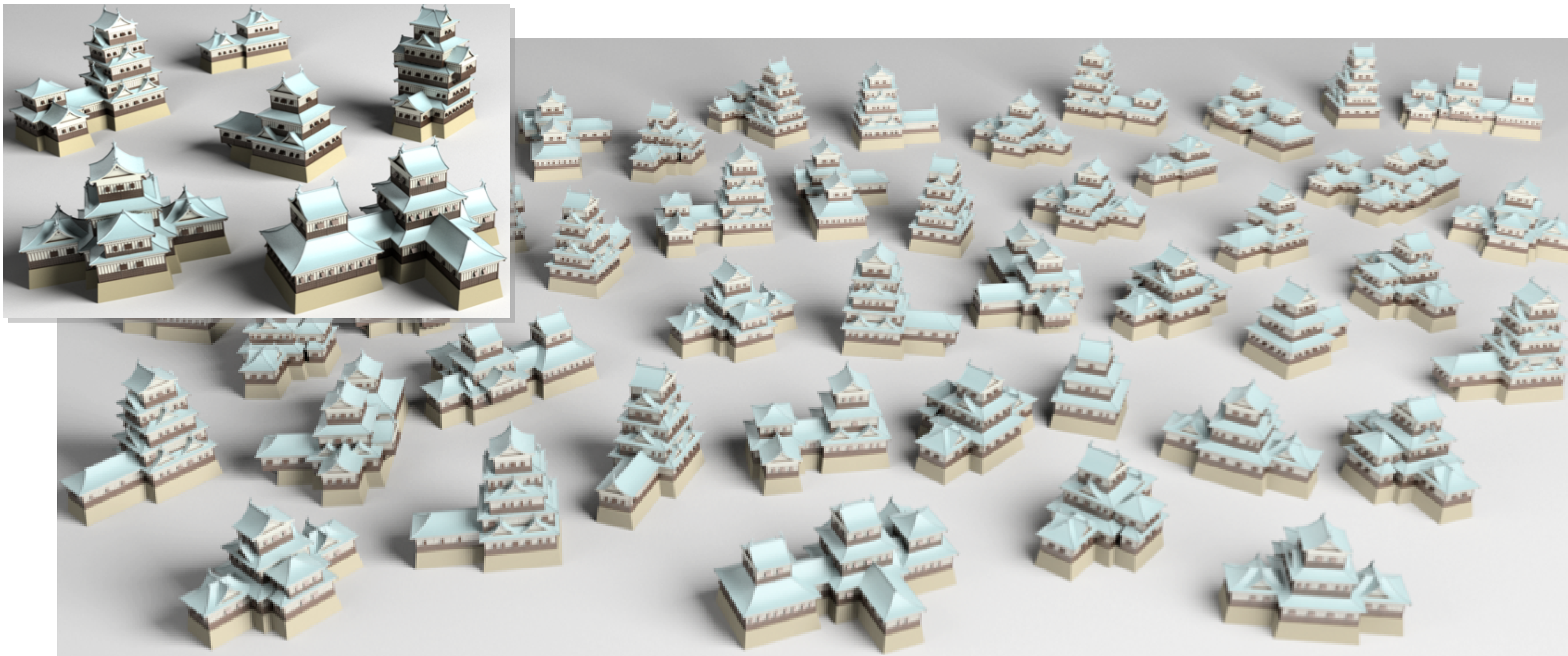
Generality: **Moderate** | Meaningful parametrization: **Yes**

Probabilistic: **Yes** | Data-driven: **Reuse**

Müller et al., 2006

Design Space: Probabilistic Grammar

(learned from examples)



Generality:	**Moderate**	Meaningful parametrization:	**Moderate**
Probabilistic:	**Yes**	Data-driven:	**Yes**

Talton et al., 2012

Design Space: Assembly-Based Modeling

(piece together existing components)

Generality: **Moderate**

Probabilistic: **No**

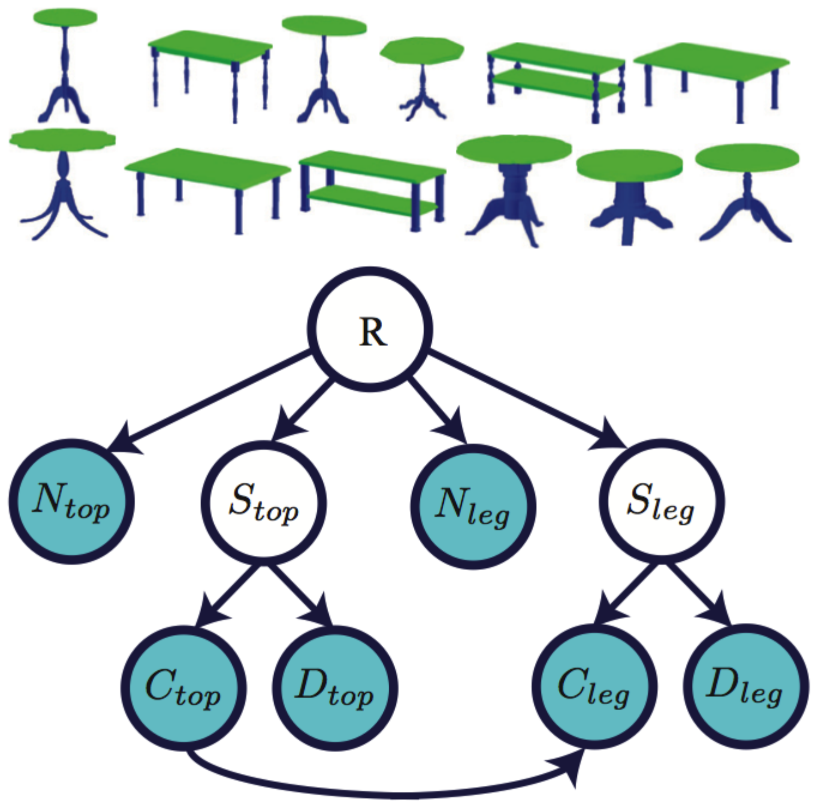
Meaningful parametrization: **Yes**

Data-driven: **Reuse**

Spore, Maxis 2008

Design Space: Probabilistic Assembly

(some assemblies are better than others)



Generality: **Moderate**

Probabilistic: **Yes**

Meaningful parametrization: **Yes**

Data-driven: **Yes**

Kalogerakis, Chaudhuri, Koller and Koltun, 2012

Design Space: Probabilistic Assembly

(some assemblies are better than others)

Learned shape styles

Learned component styles

Generality:	**Moderate**	Meaningful parametrization:	**Yes**
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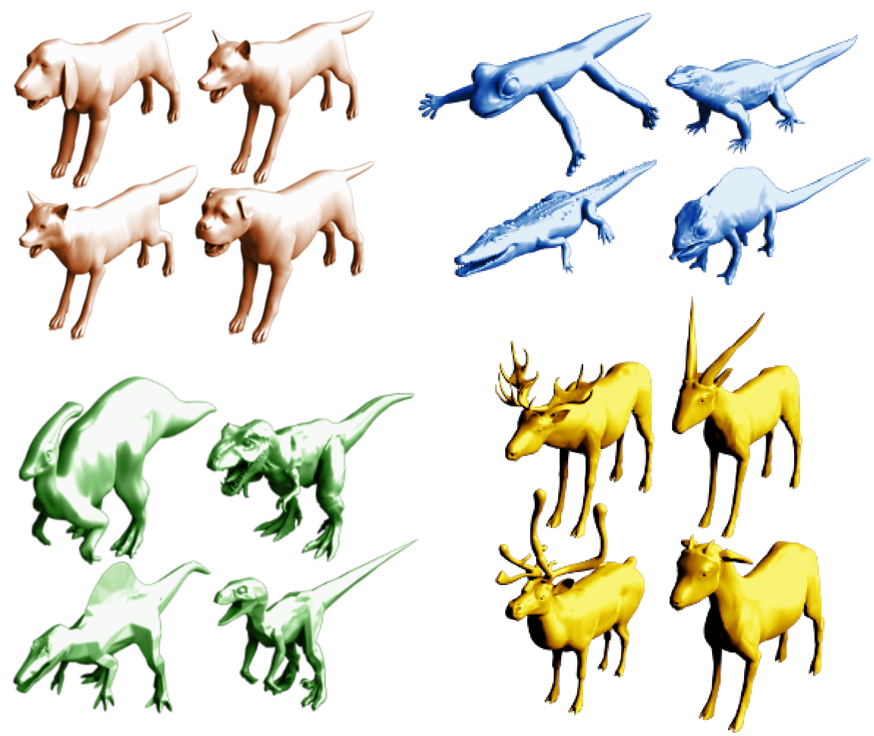

More learned shape “styles”

Generality: **Moderate**

Probabilistic: **Yes**

Meaningful parametrization: **Yes**

Data-driven: **Yes**

Kalogerakis, Chaudhuri, Koller and Koltun, 2012

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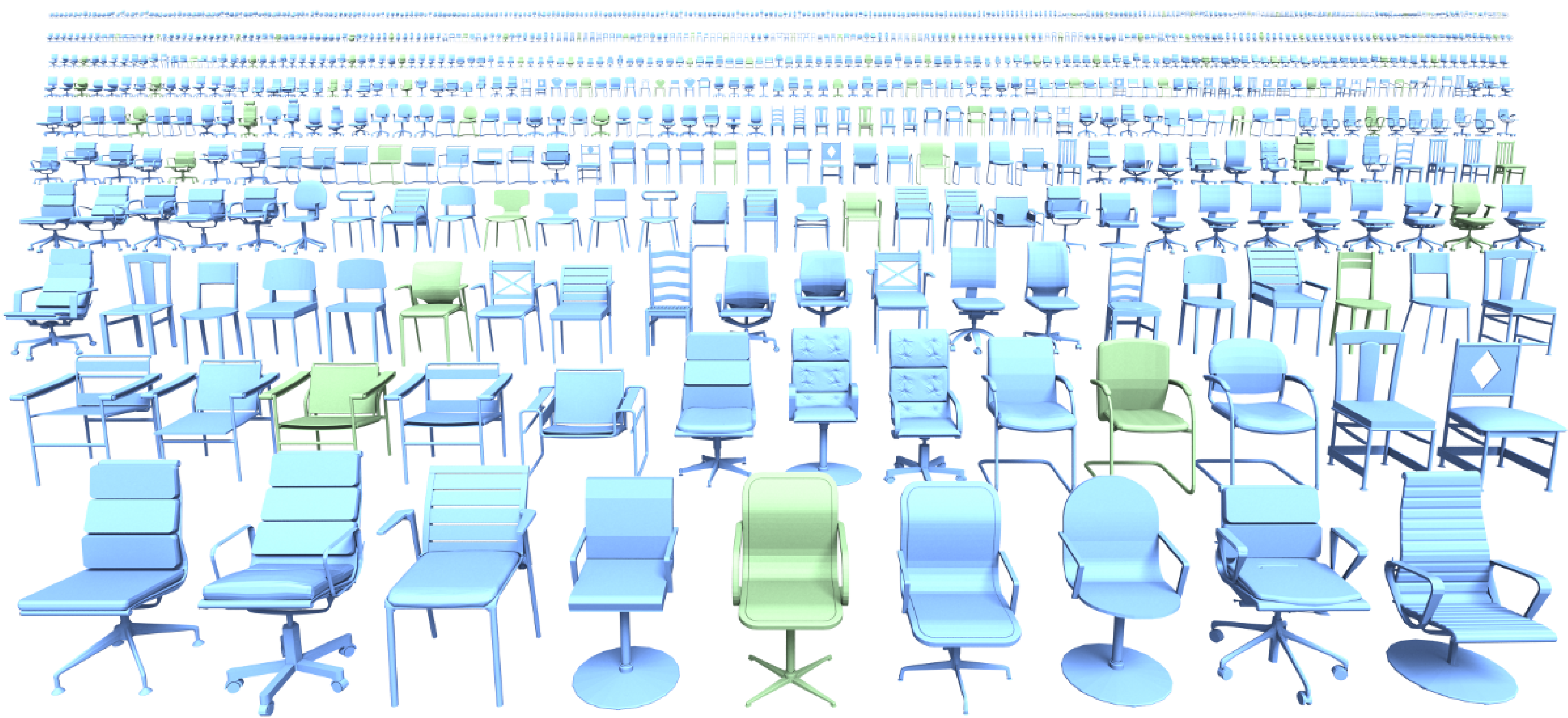

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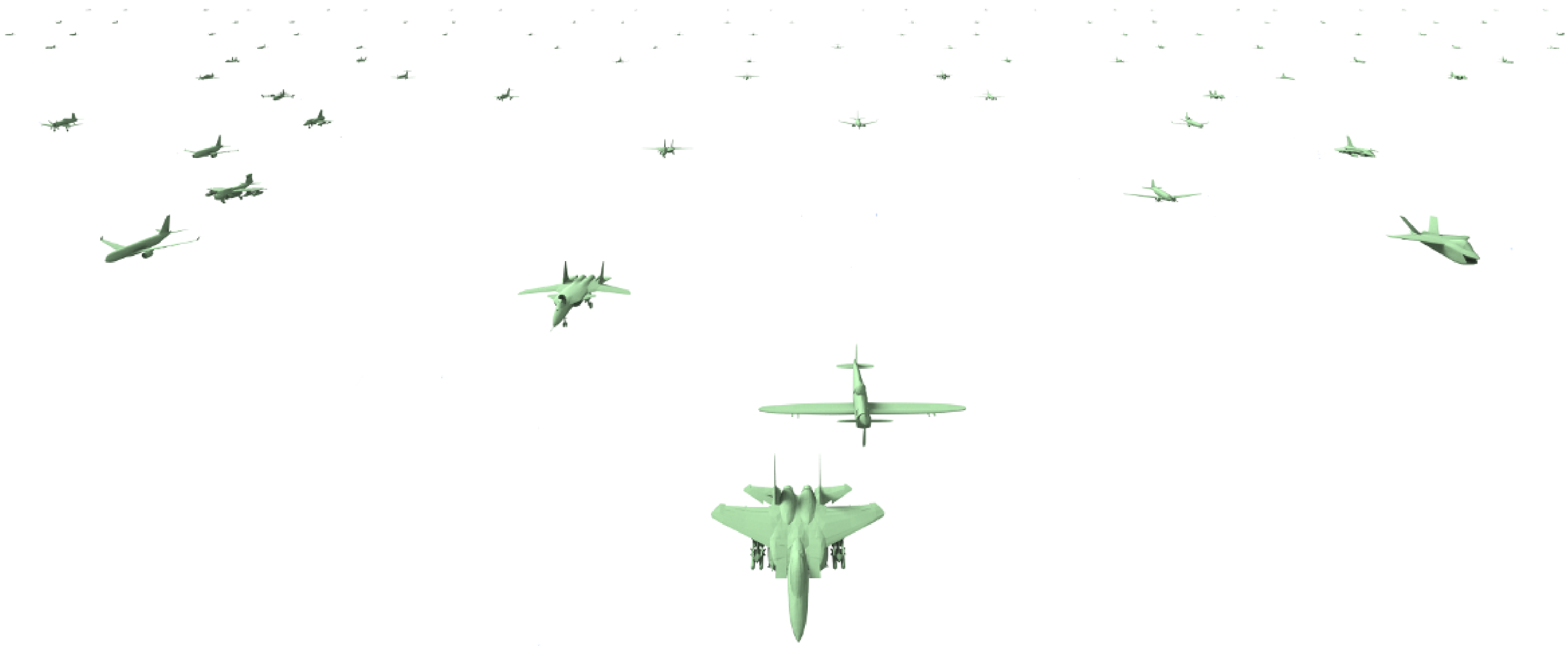

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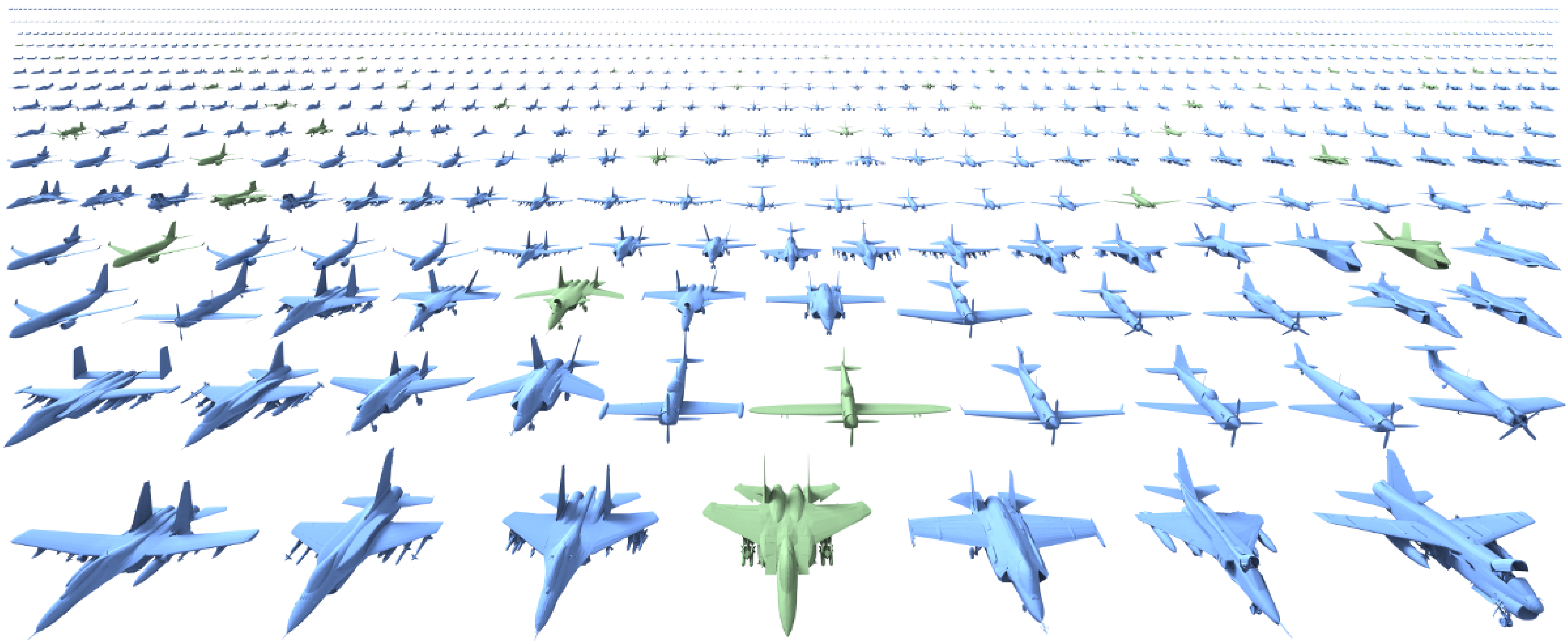

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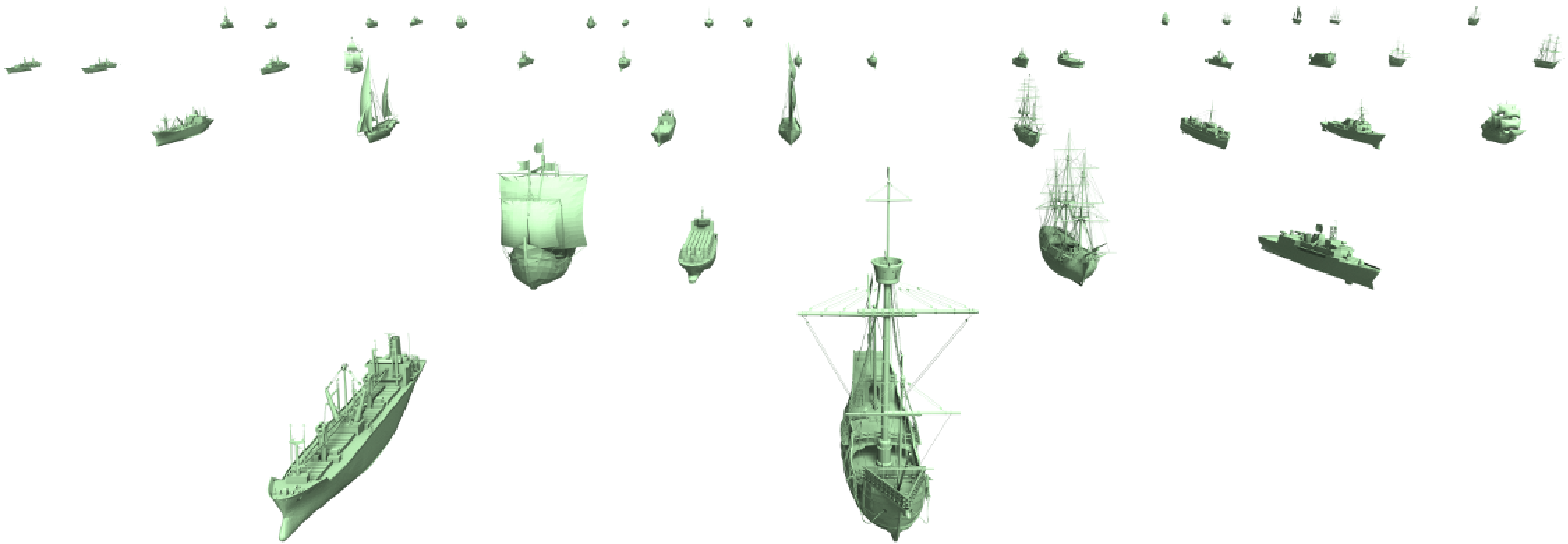

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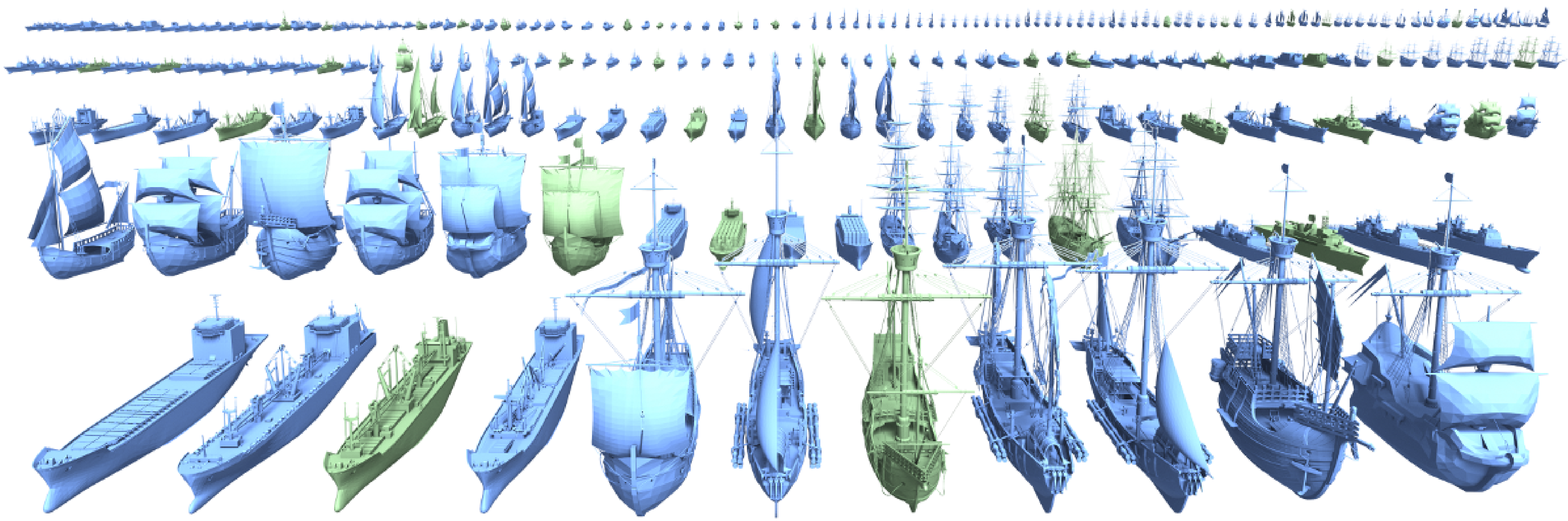

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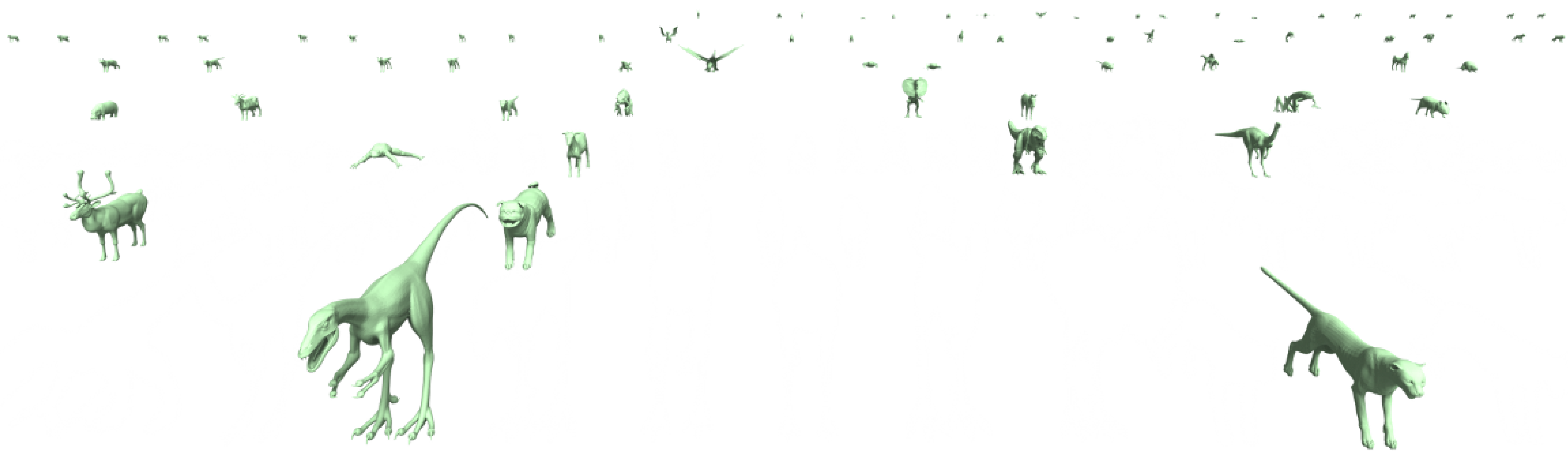

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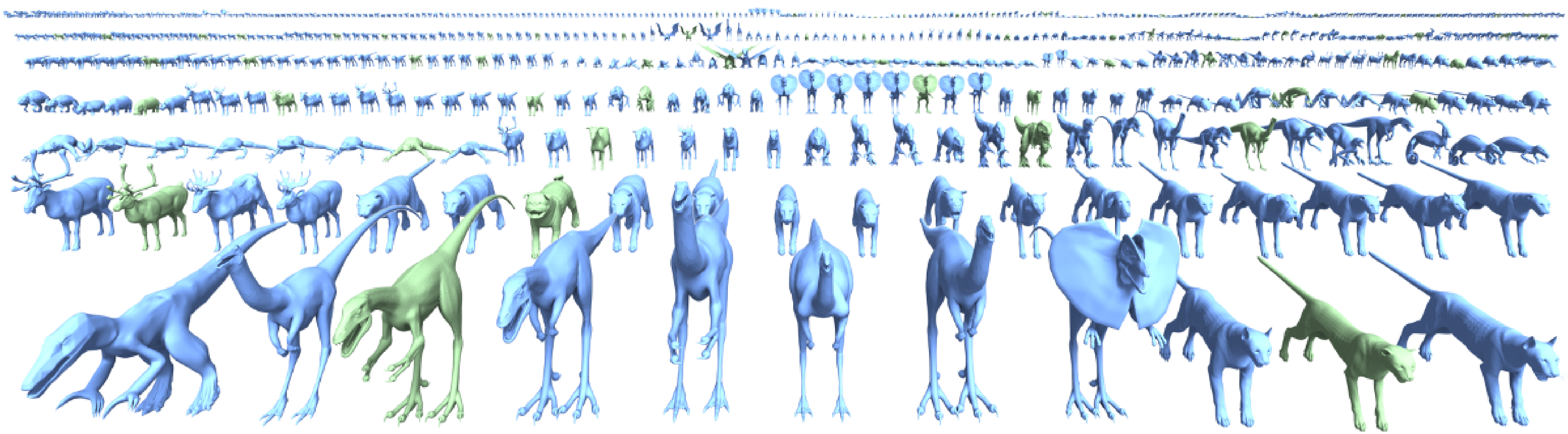

Generality: **Moderate**
Probabilistic: **Yes**
Meaningful parametrization: **Yes**
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Kalogerakis, Chaudhuri, Koller and Koltun, 2012

- Make a cute toy

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- Make an aerodynamic airplane

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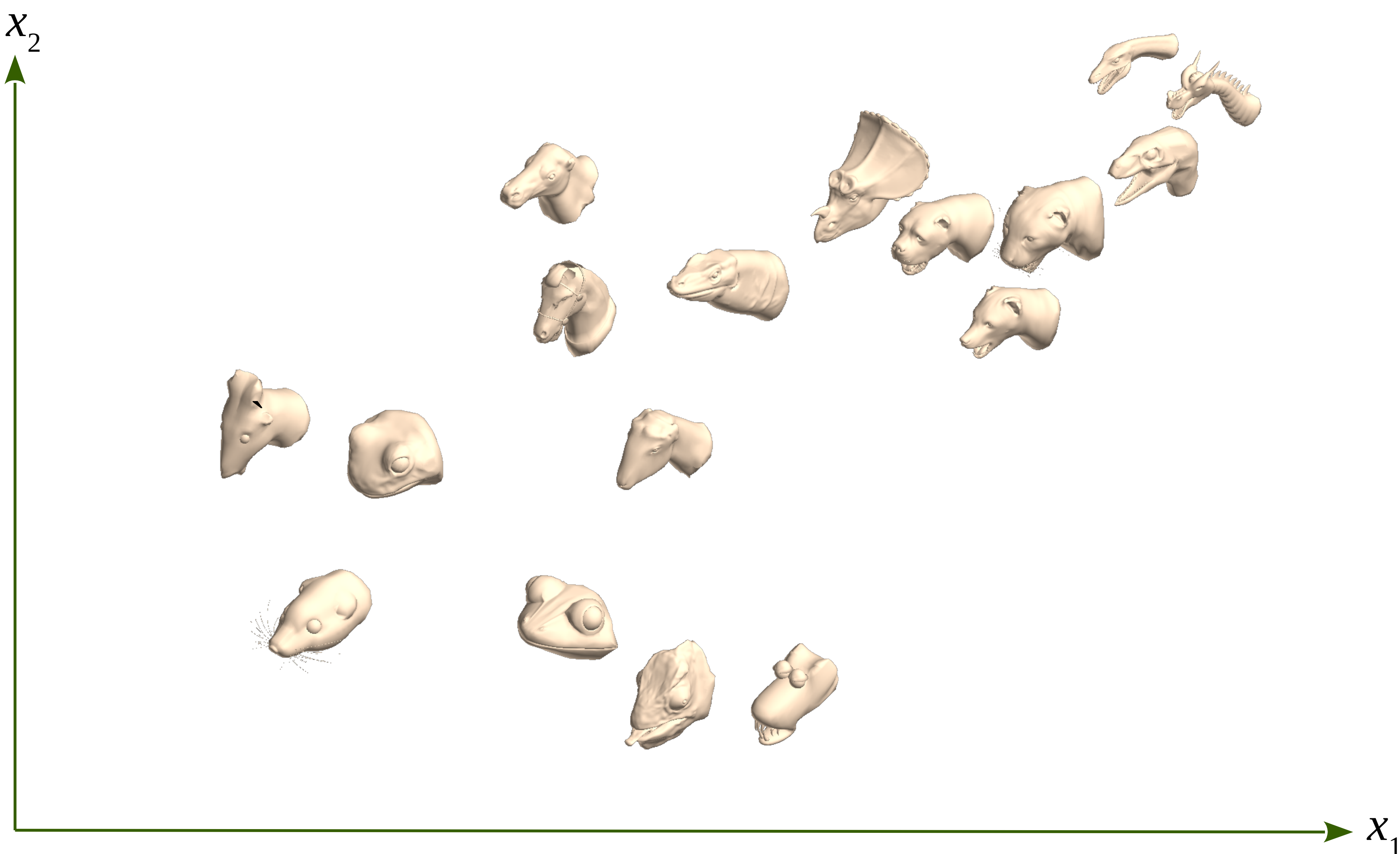
Semantic Basis for Design Space



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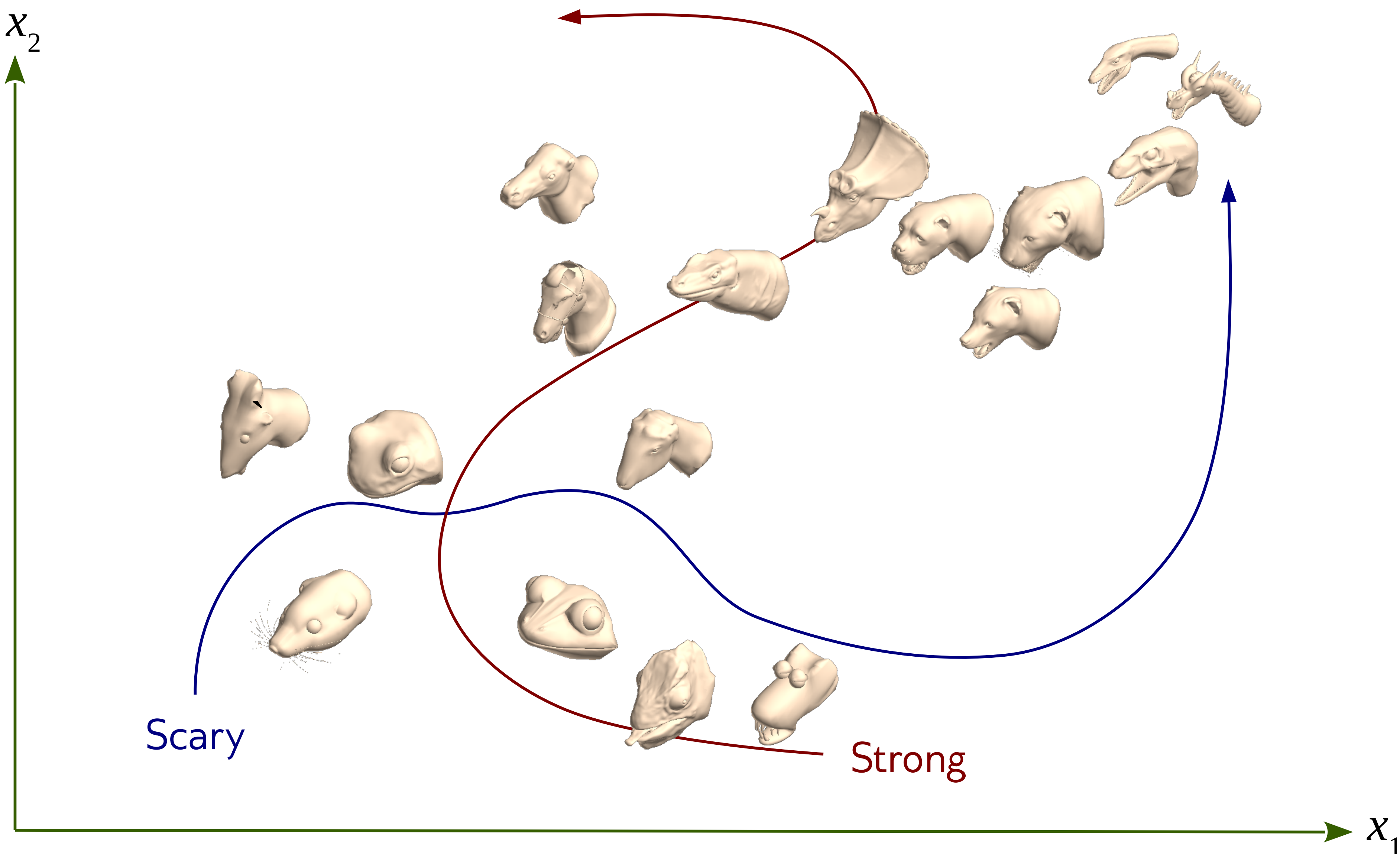

A cute toy for a small child

Chaudhuri, Kalogerakis, Giguere and Funkhouser, 2013

Learning Semantic Attributes

- Crowdsource **comparative adjectives**
  - Amazon Mechanical Turk
  - Schelling survey

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Learning Semantic Attributes

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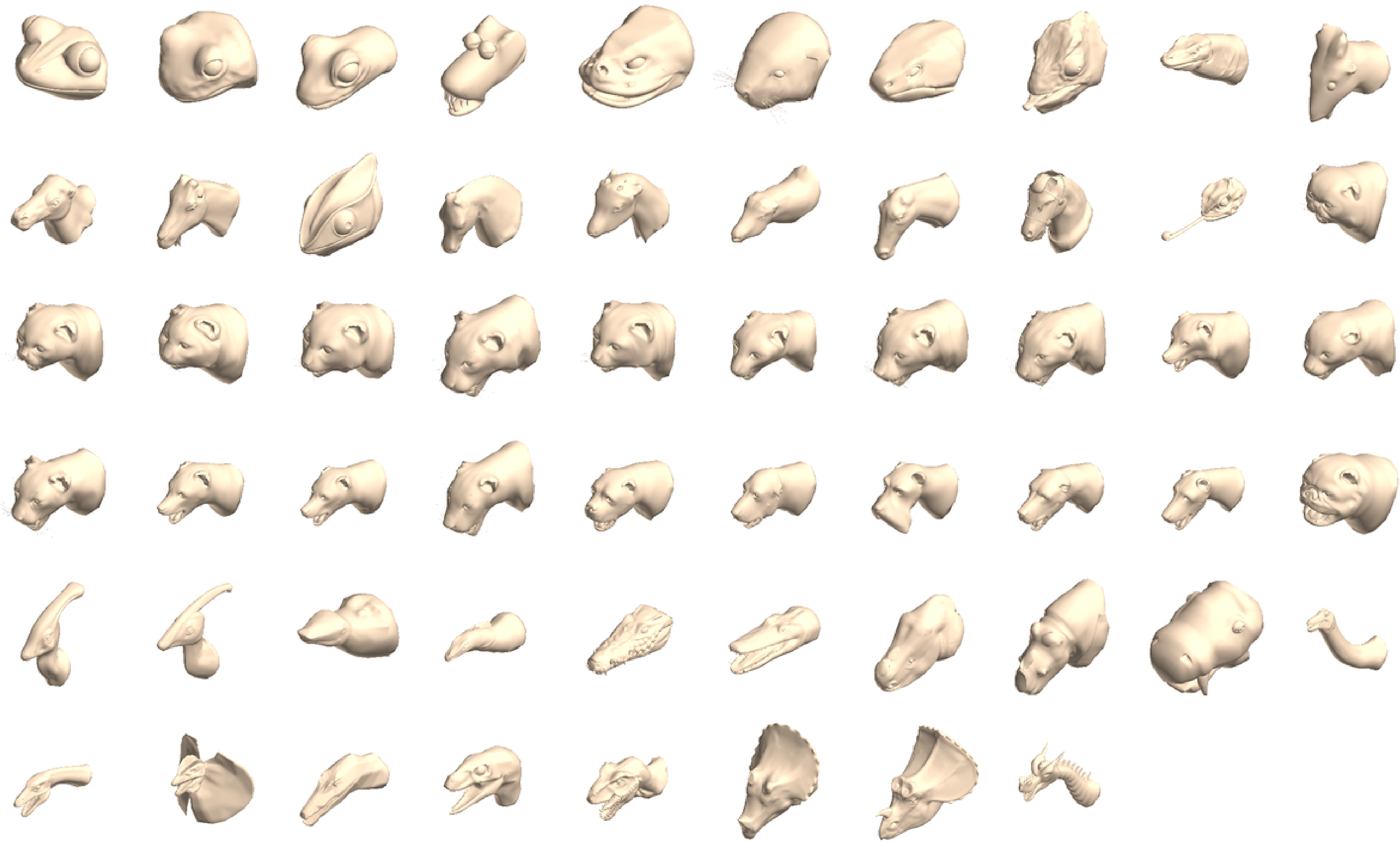
- Learn **ranking functions**
  - f: shape features $\rightarrow \mathbb{R}$
  - Rank-SVM with transformed features & sigmoid loss
  - Iterate with cross-correlation between attributes
  - Extend to multi-component rankings

“Dangerous”



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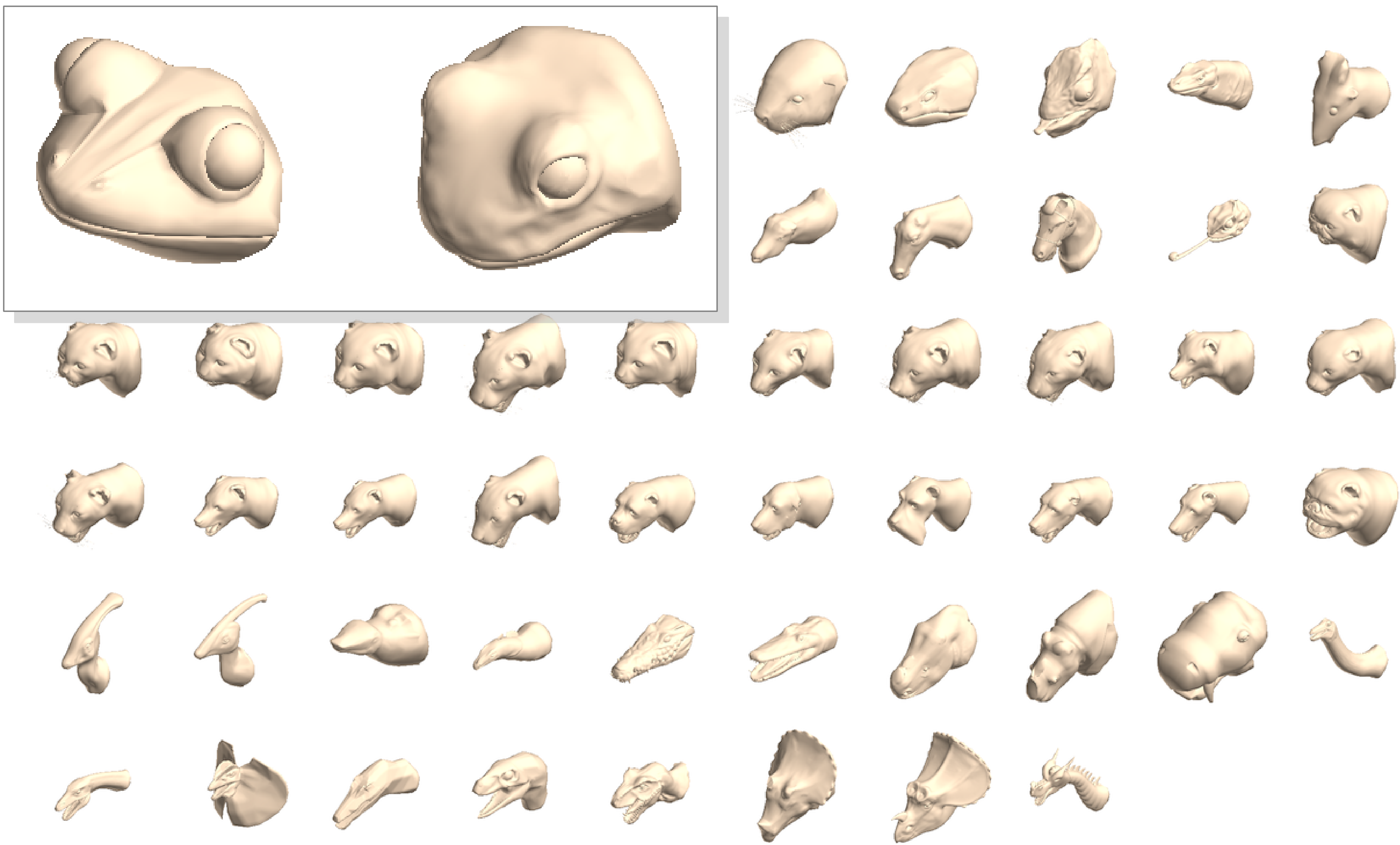

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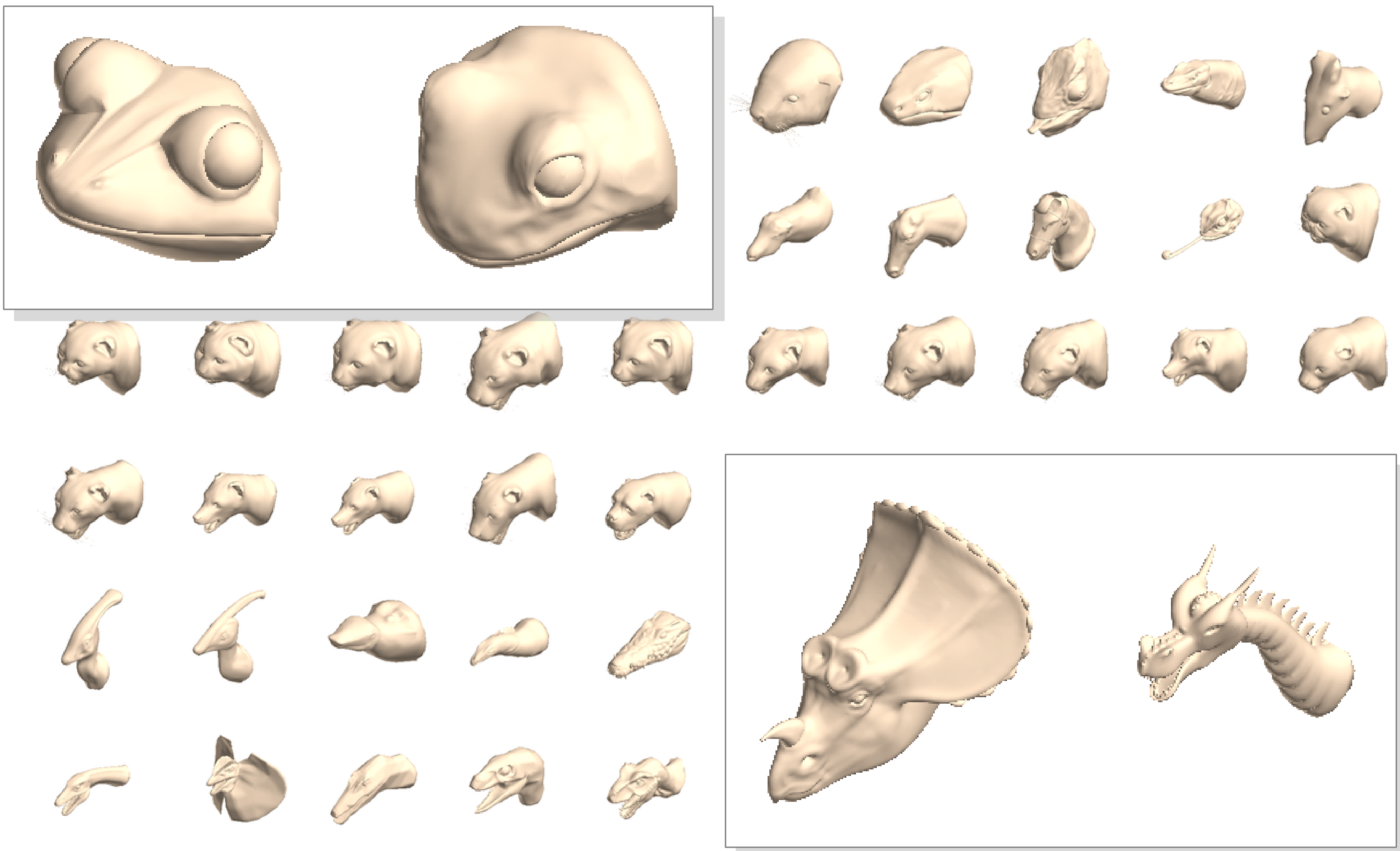

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“Old-fashioned”

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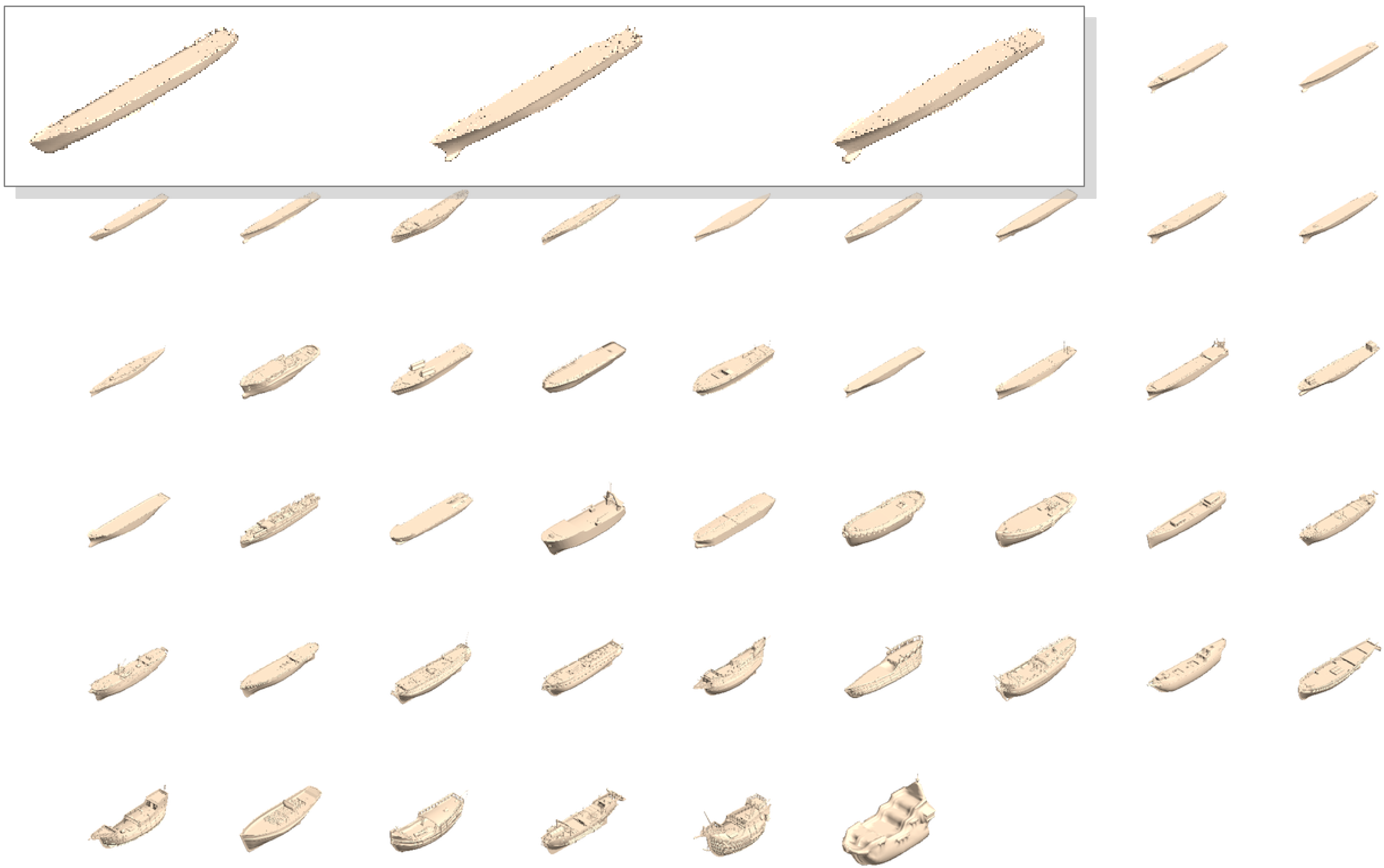

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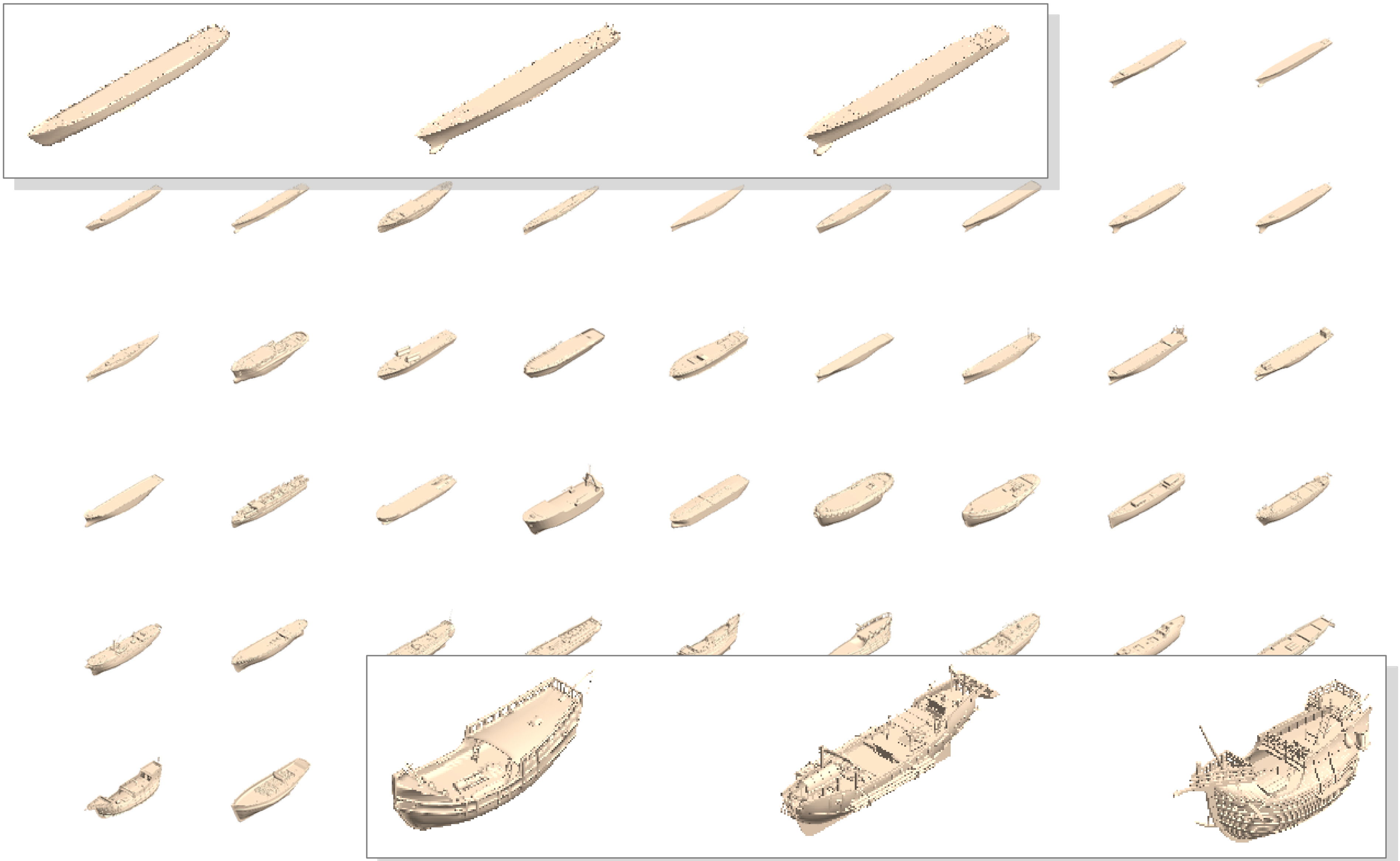
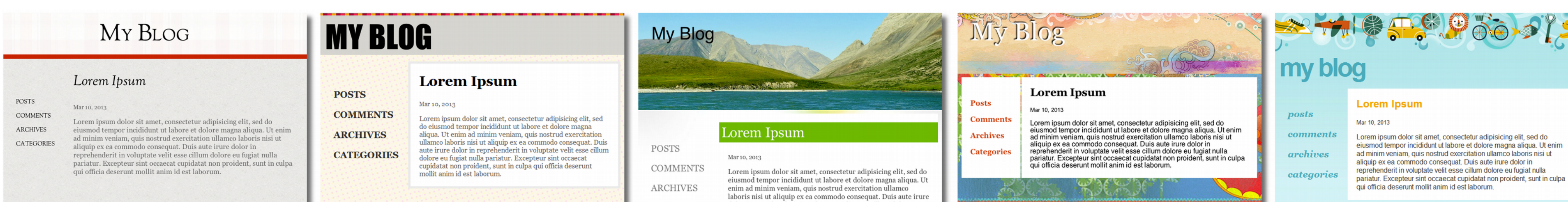


Chaudhuri, Kalogerakis, Giguere and Funkhouser, 2013

Web Design with Semantic Attributes

Attributes: artistic, casual, cheerful, colorful, creative, cute, elegant, emphatic, modern, professional, romantic, simple, welcoming

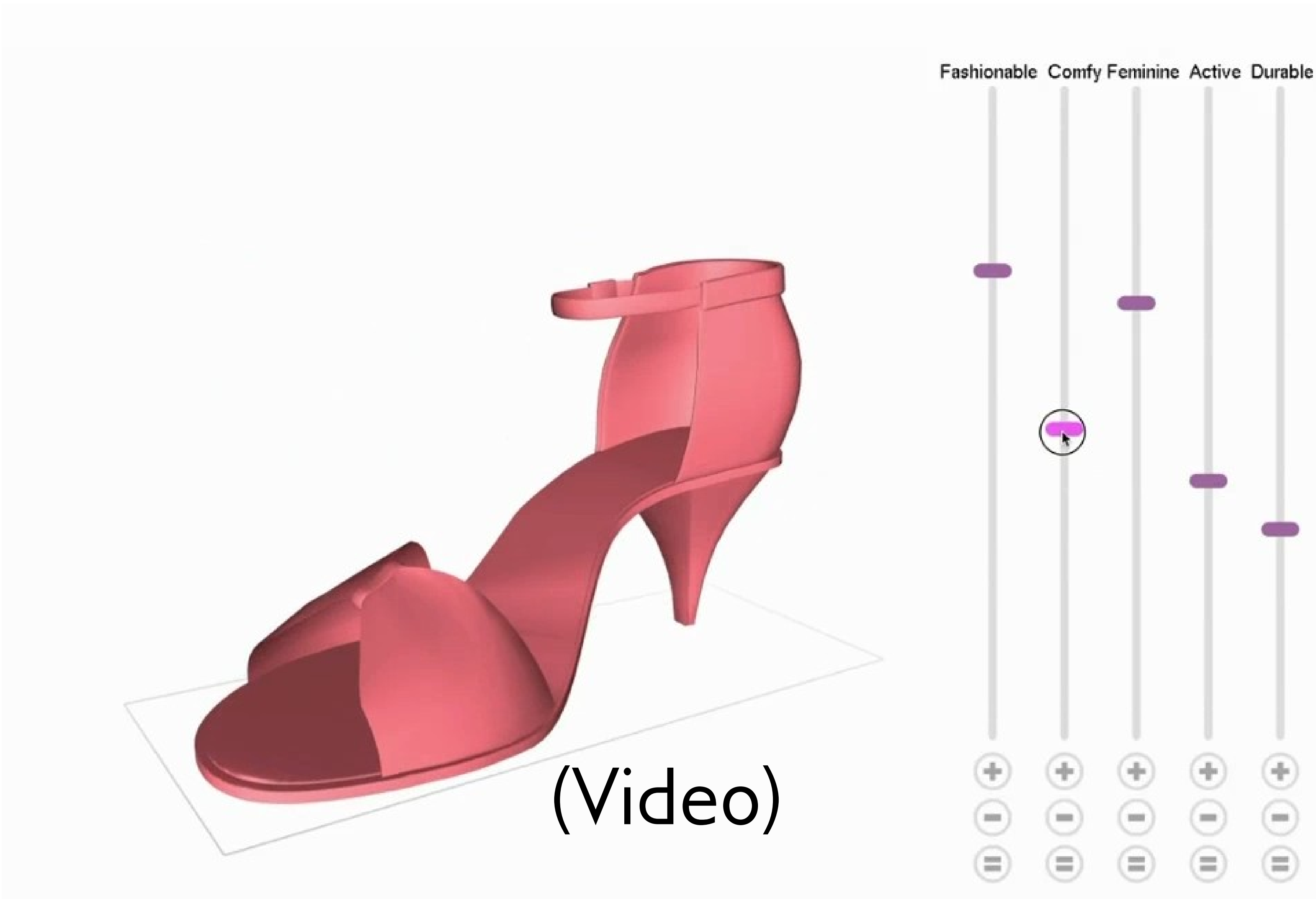
Less "artistic" ⟷ More "artistic"



Less "casual" ⟷ More "casual"

Chaudhuri, Kalogerakis, Giguere and Funkhouser, 2013

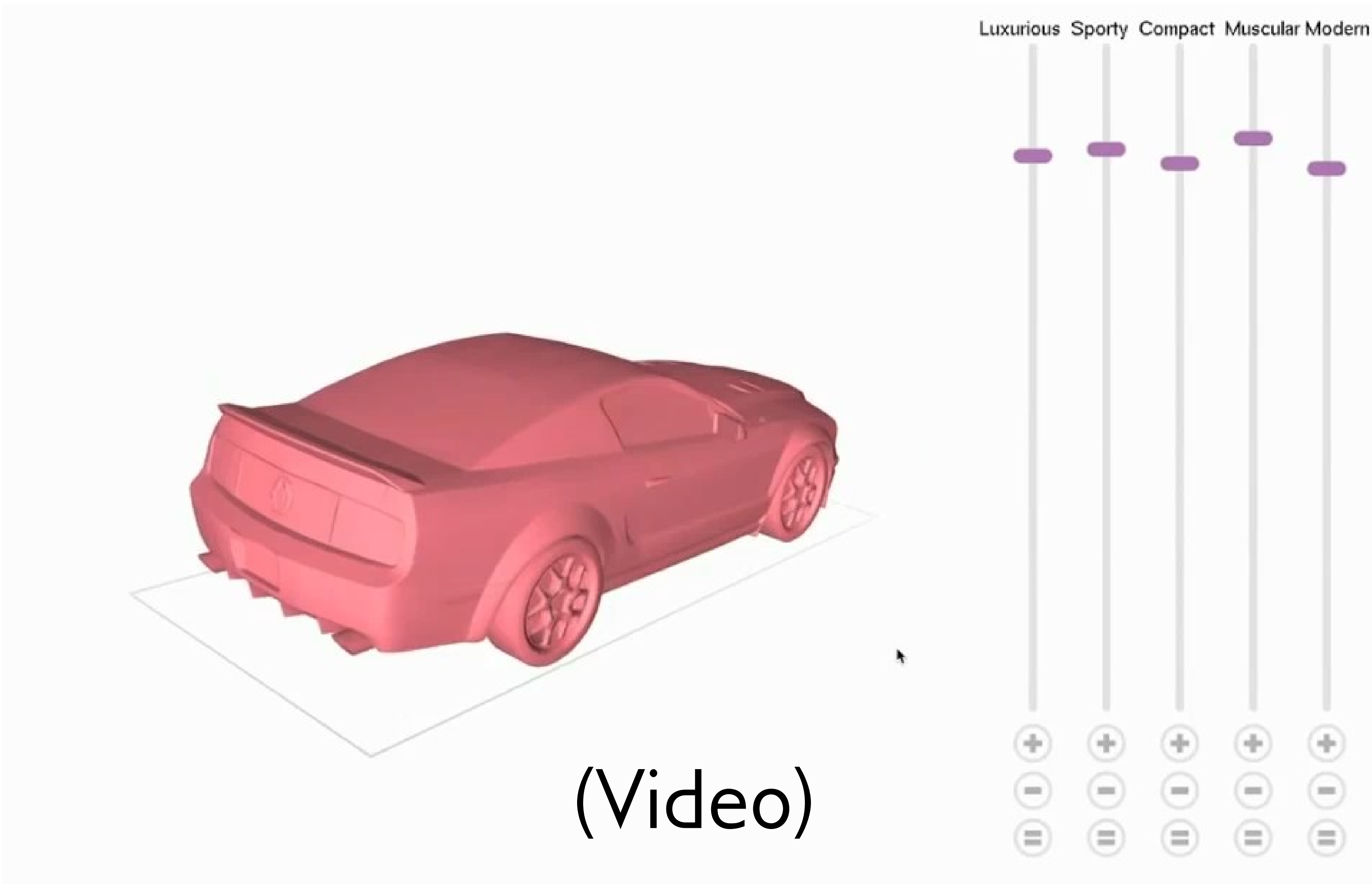
Continuous Deformation: Shoes



(Video)

Yumer, Chaudhuri, Hodgins and Kara, SIGGRAPH 2015

Continuous Deformation: Cars



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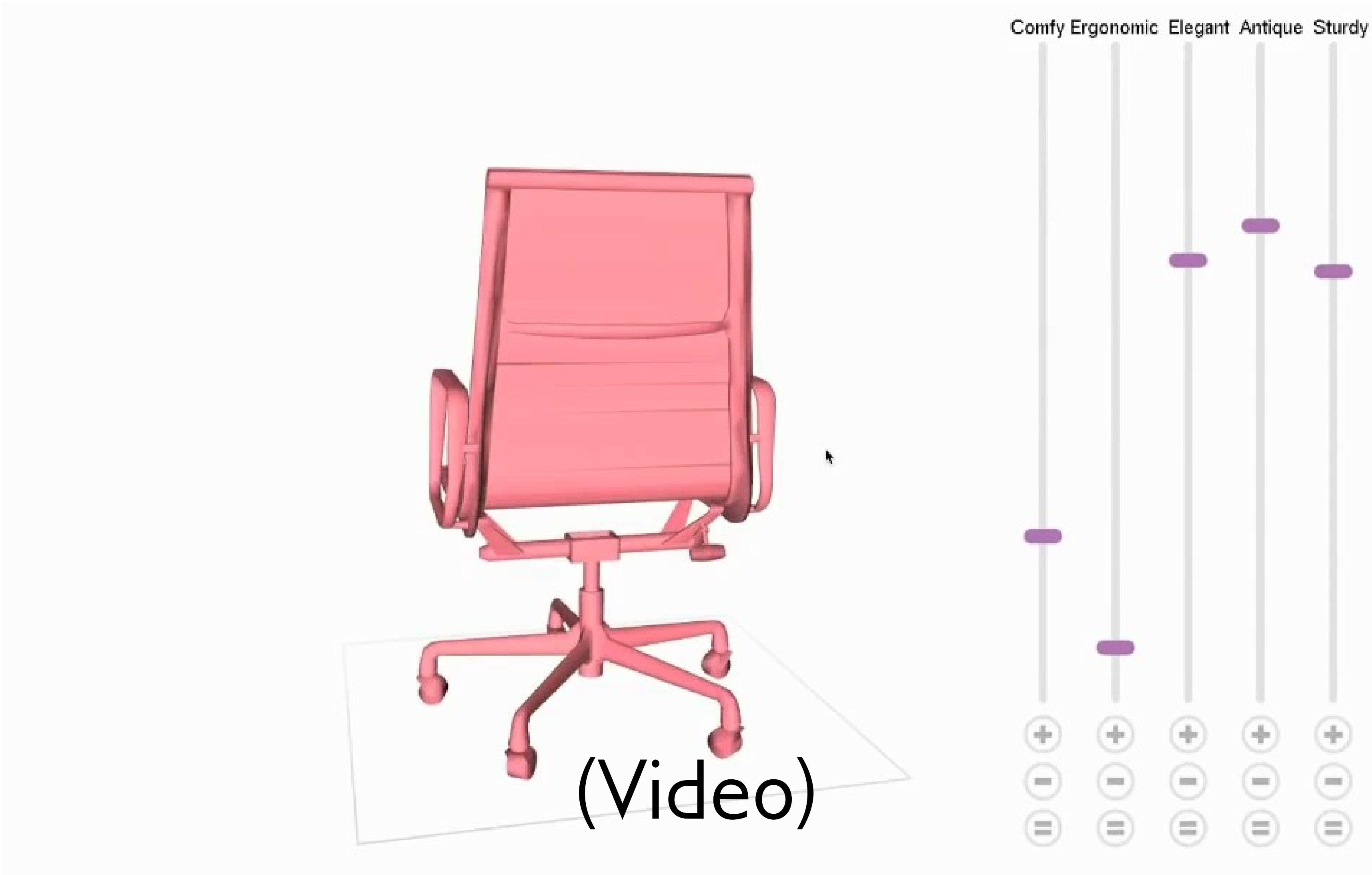
Continuous Deformation: Chairs



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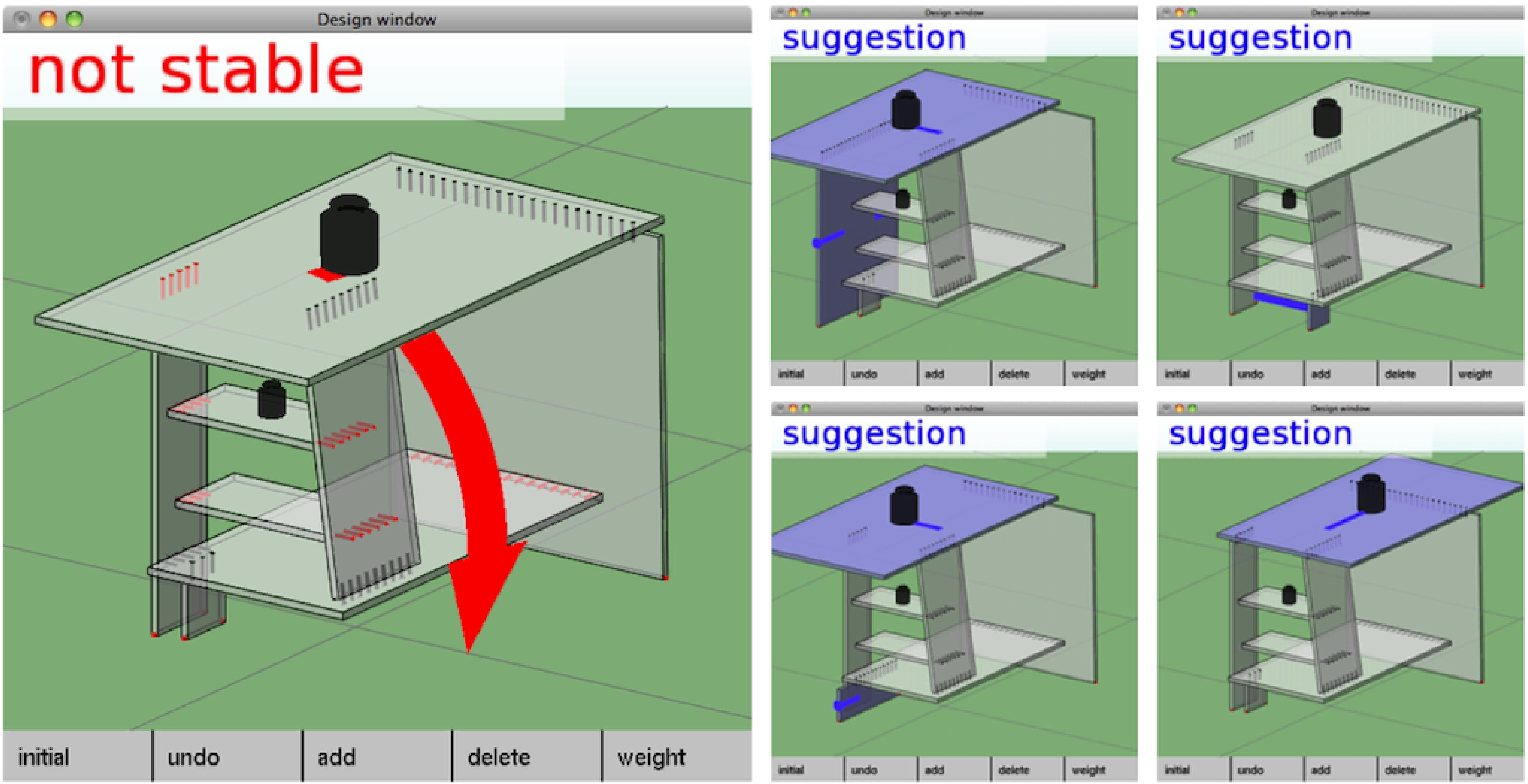
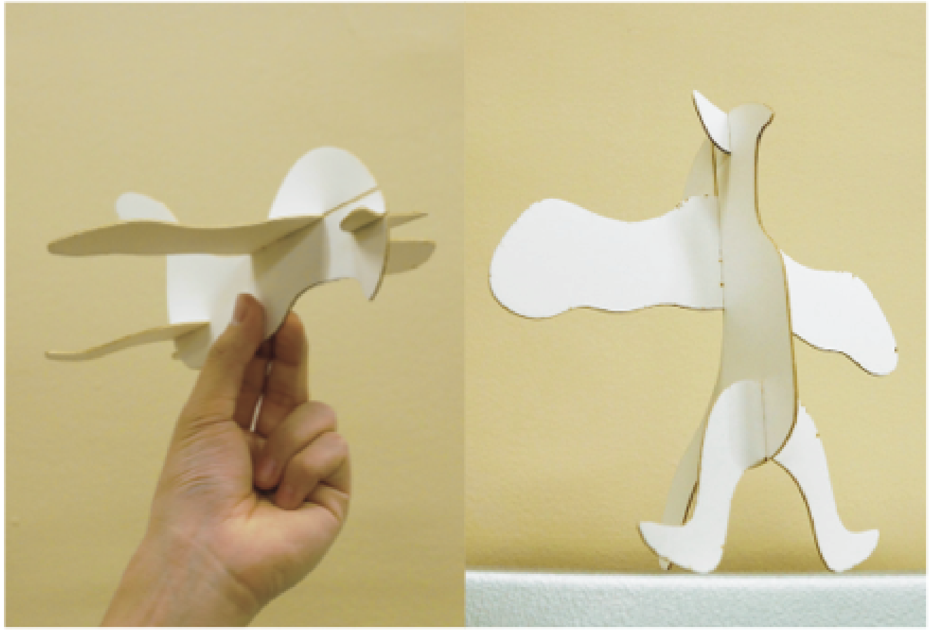
Designing for Mechanical Function



Umetani, Igarashi and Mitra, 2012

Designing for Mechanical Function



Umetani, Koyama, Schmidt and Igarashi, 2014

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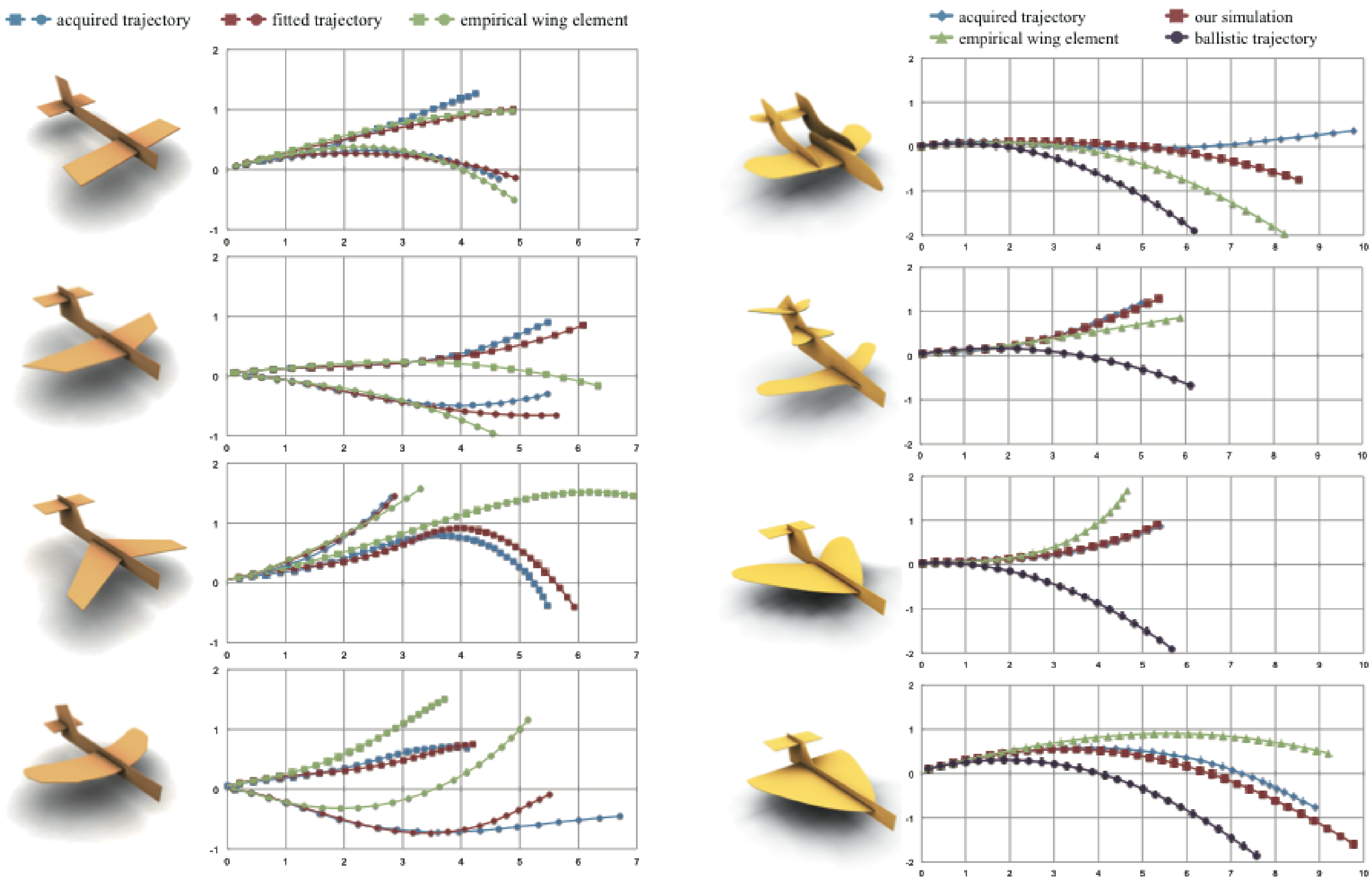

Umetani, Koyama, Schmidt and Igarashi, 2014

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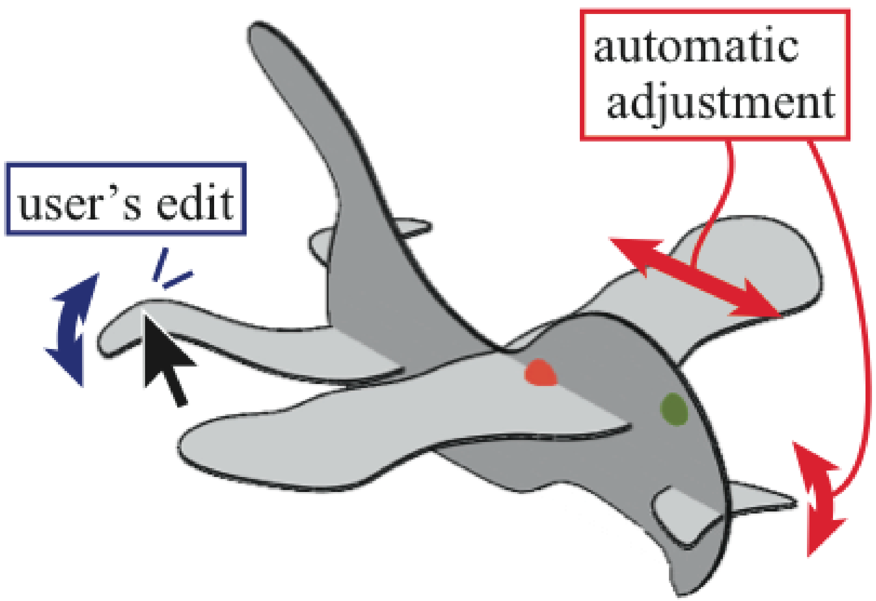
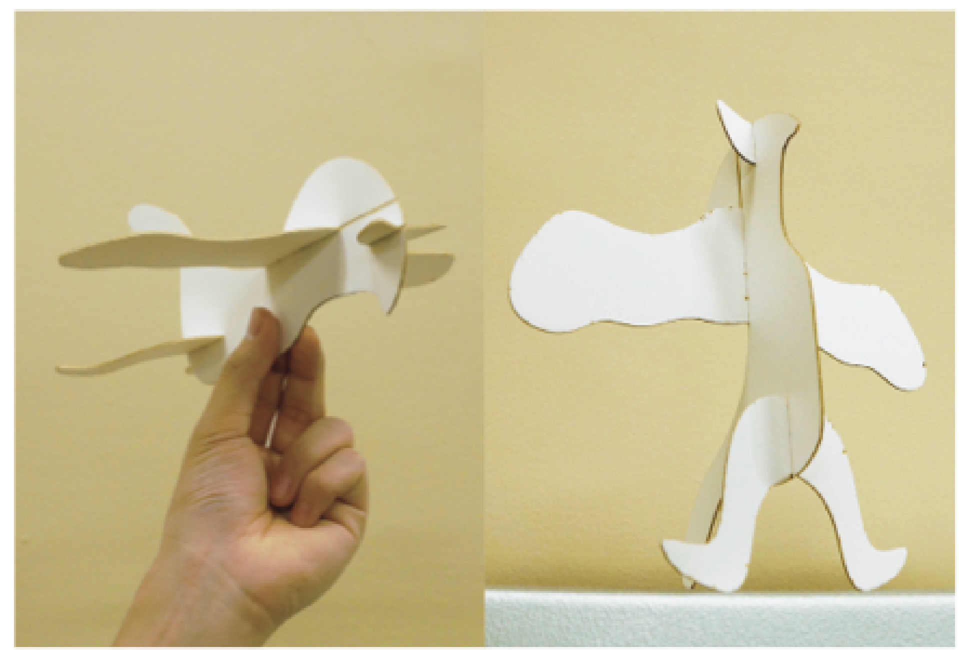
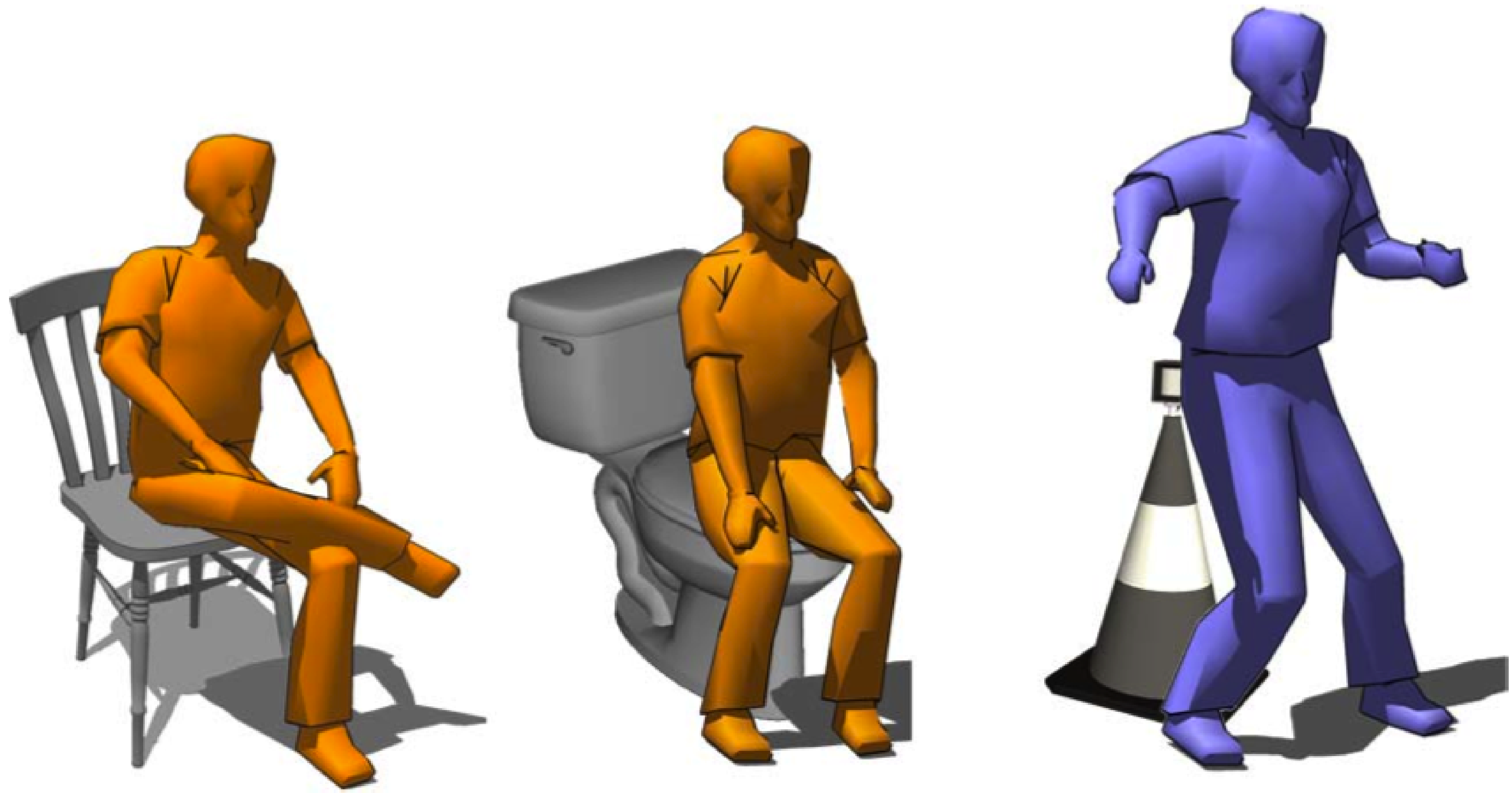




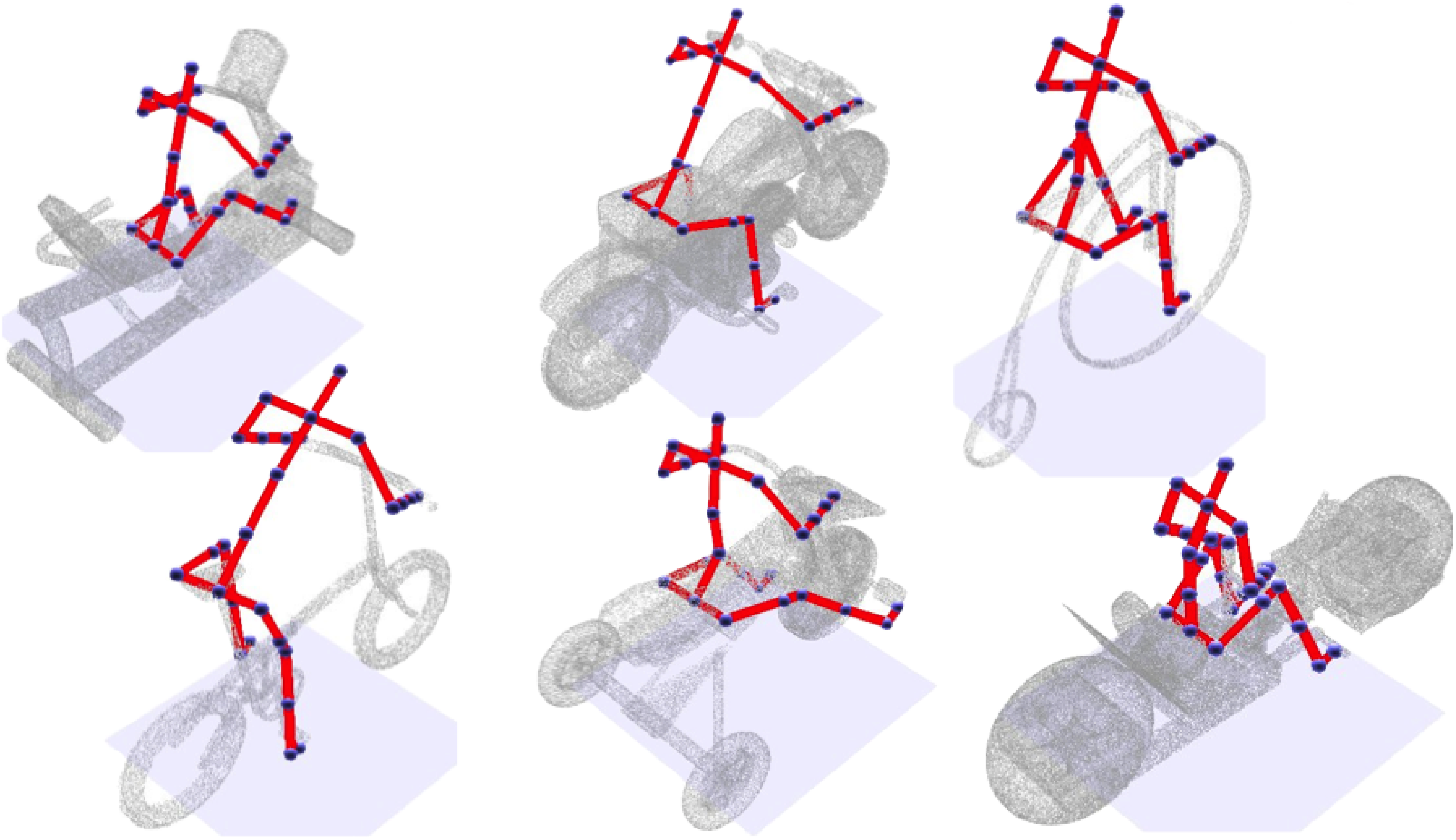
Umetani, Koyama, Schmidt and Igarashi, 2014

What makes a chair a chair?



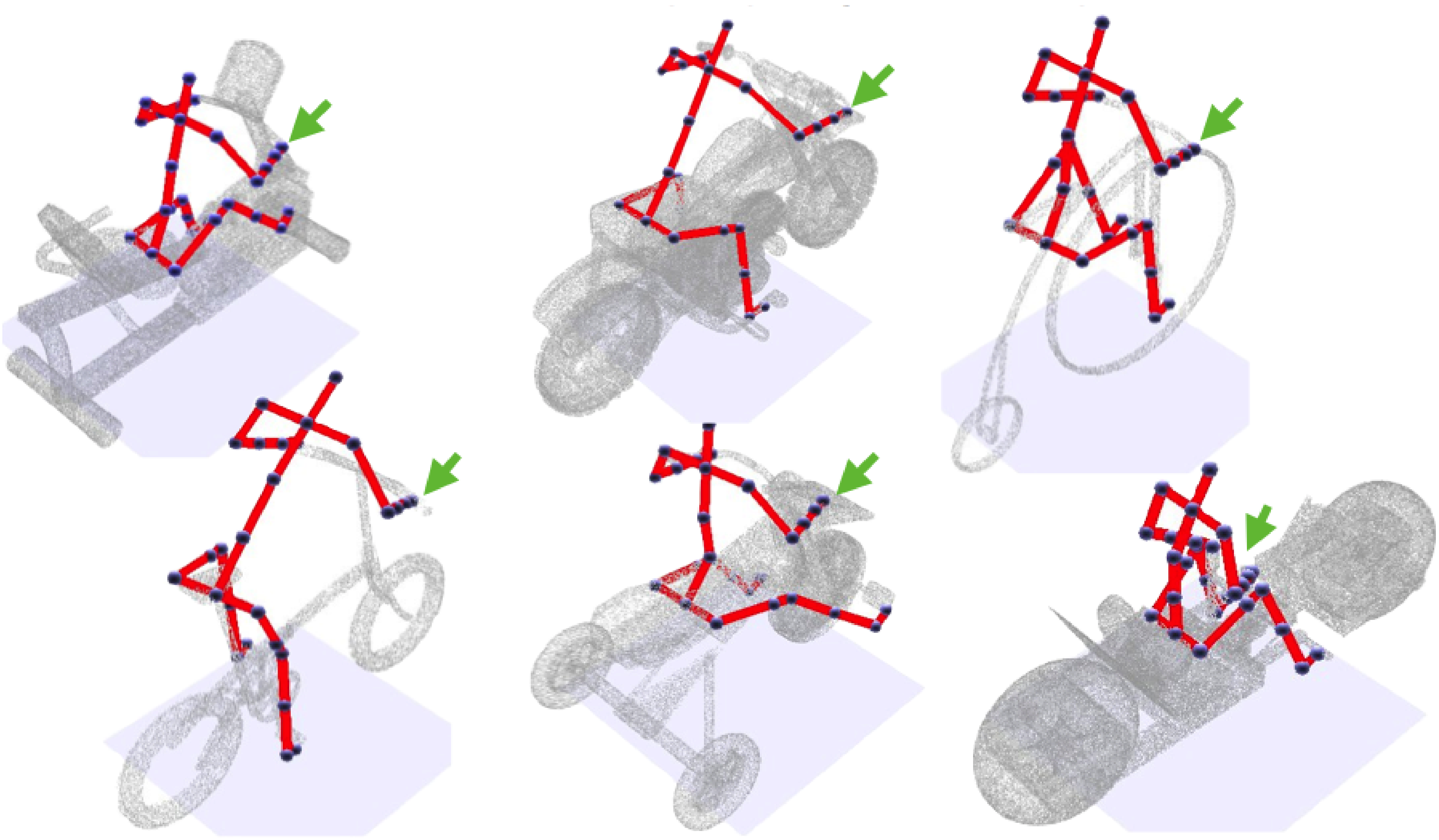
Grabner, Gall and Van Gool, 2011

Human-Centric Shape Analysis



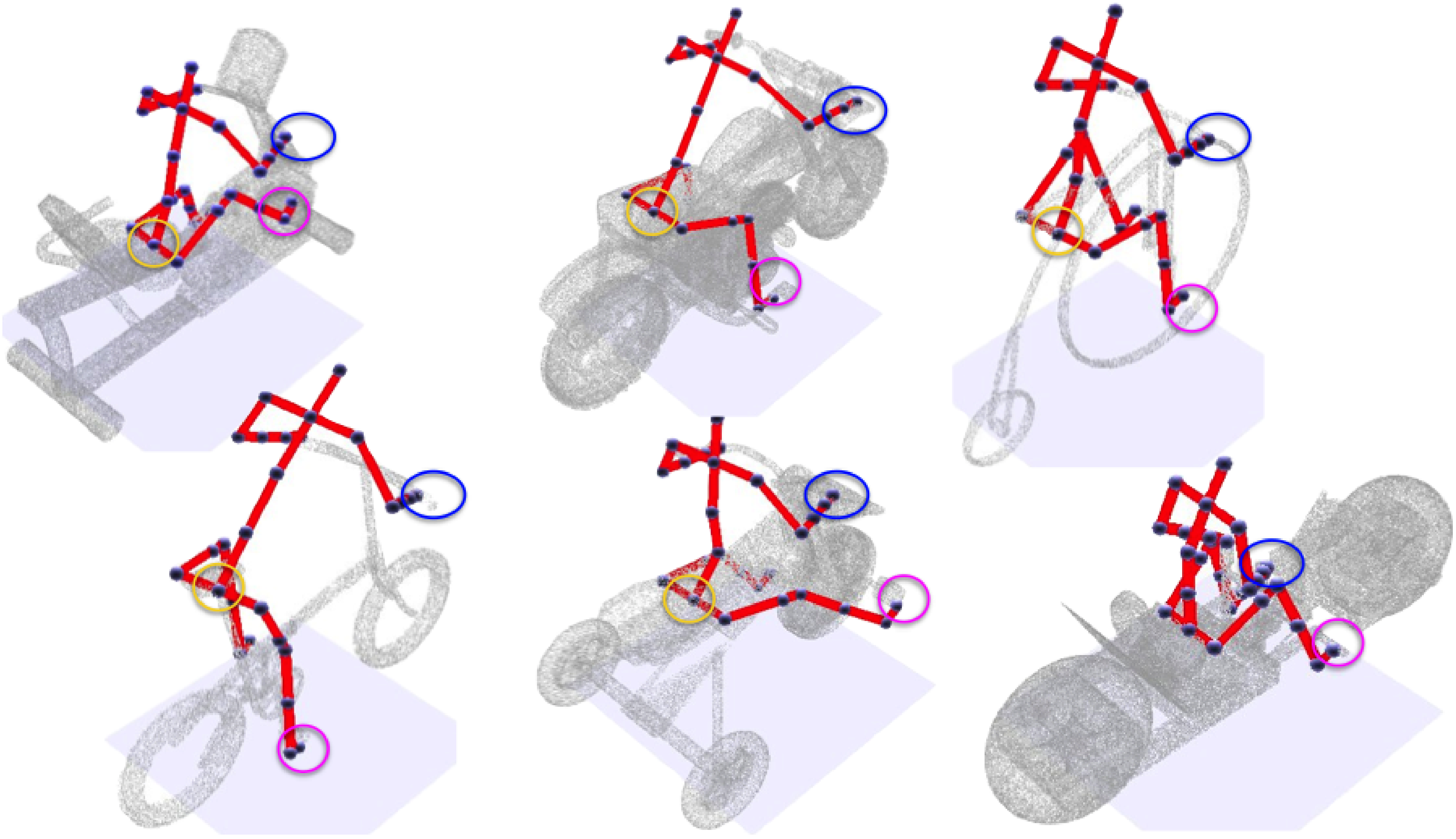
Kim, Chaudhuri, Guibas and Funkhouser, 2014

Point-to-Point Correspondences



Kim, Chaudhuri, Guibas and Funkhouser, 2014

Functional Parts



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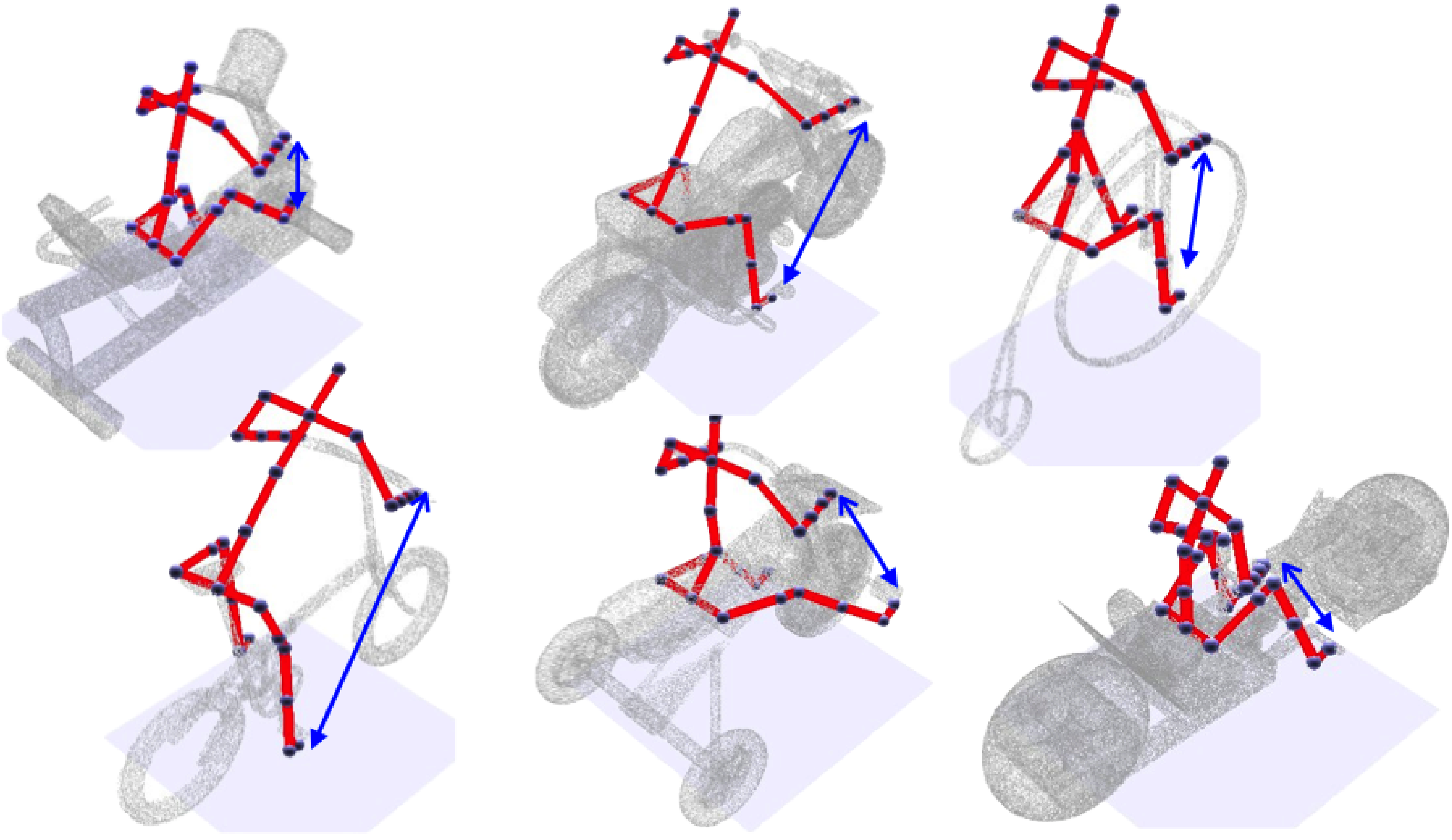
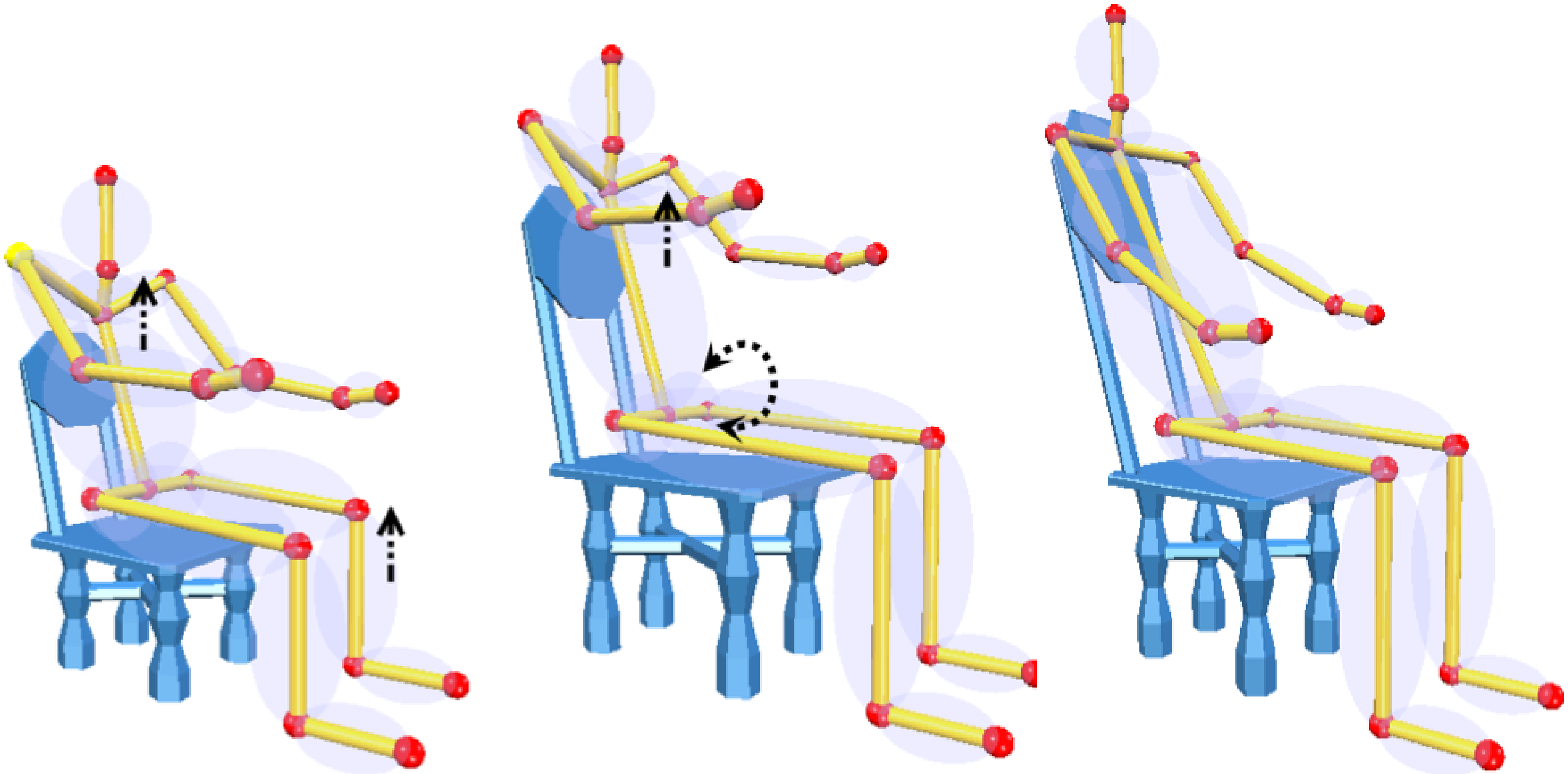
Structural Variations



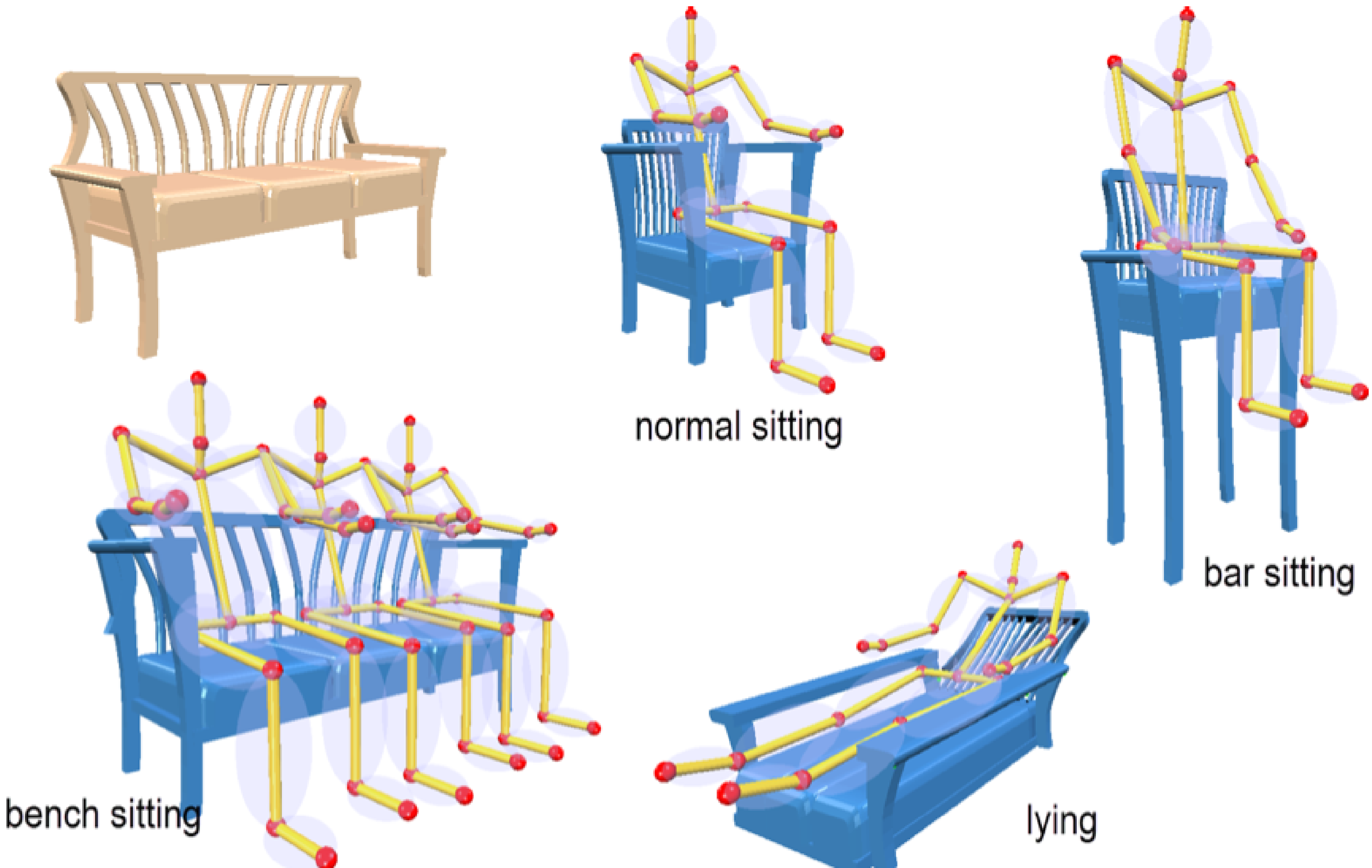
Kim, Chaudhuri, Guibas and Funkhouser, 2014

Shape Adjustment for Body Type



Zheng, Dorsey and Mitra, 2014

Shape Adjustment for Body Pose



Zheng, Dorsey and Mitra, 2014

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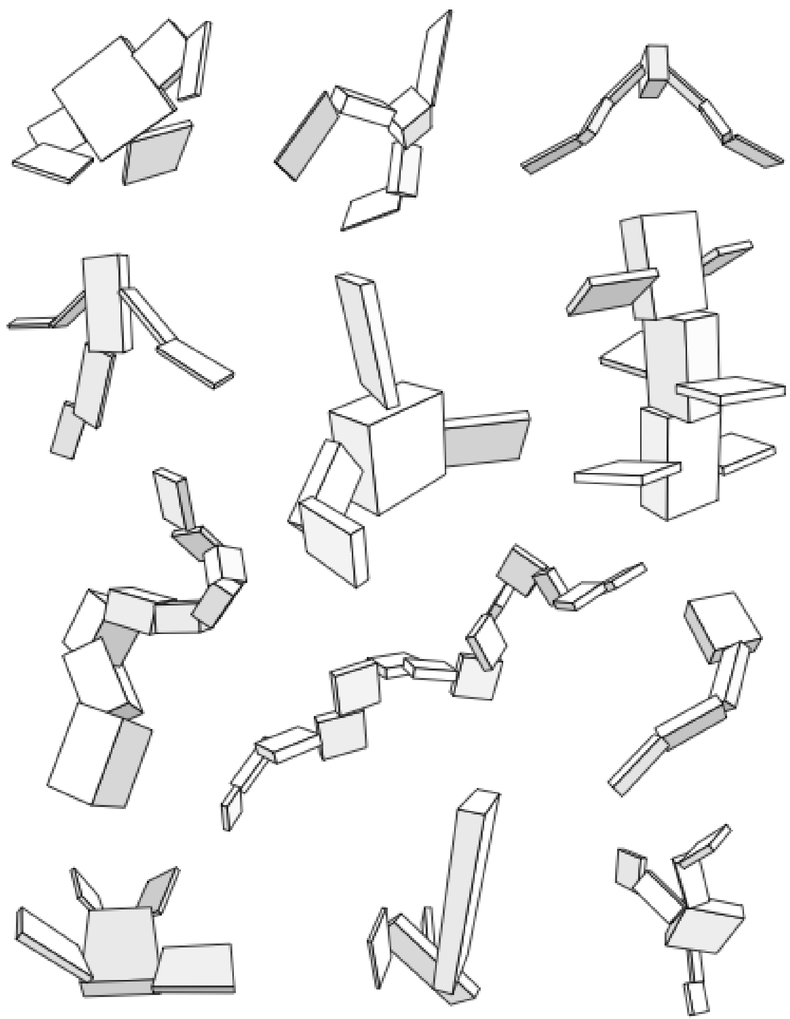
- Design intent can be captured through **semantic attributes**, **mechanical function** and **human interaction**

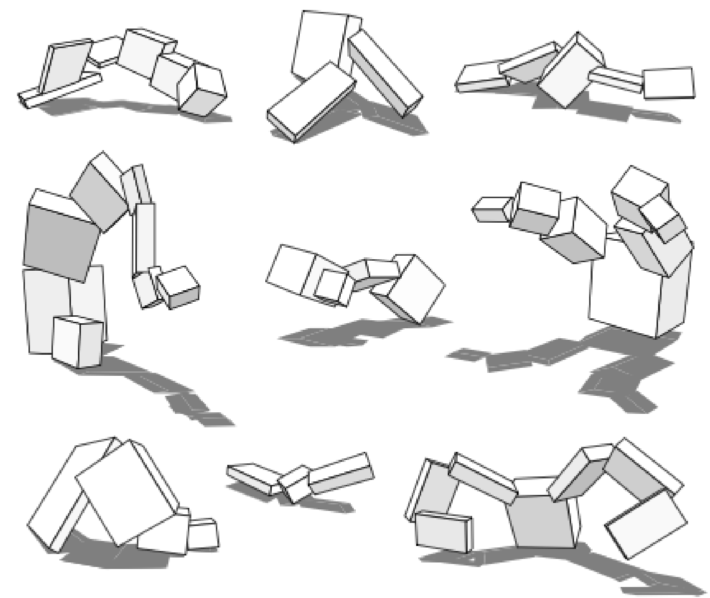
Summary

- **Design** as optimization
- **Probabilistic models** can characterize the structure of "plausible" objects
- Design intent can be captured through **semantic attributes**, **mechanical function** and **human interaction**
- Models of structure, attributes, function and interaction can be automatically learned from **(big) data**

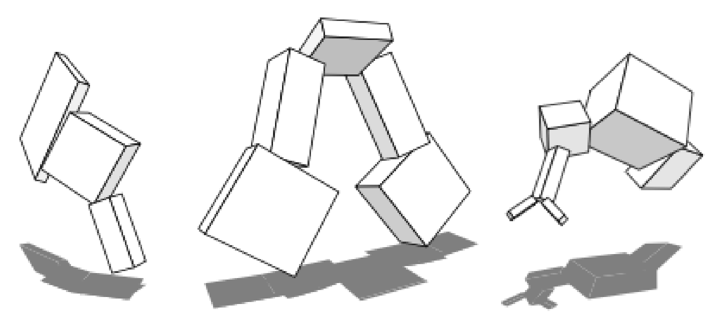
Goal-Oriented Design Evolution



Swimming



Walking



Jumping

“Evolving Virtual Creatures”, Karl Sims, SIGGRAPH 1994


(Video)