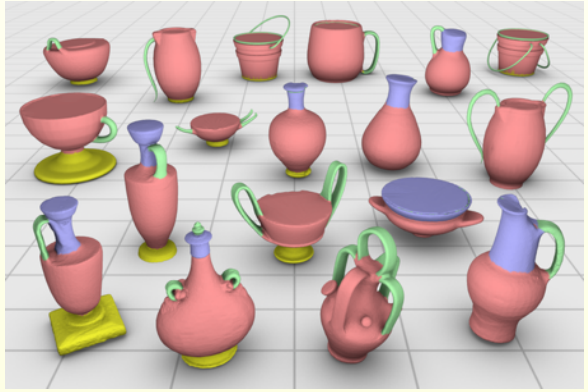
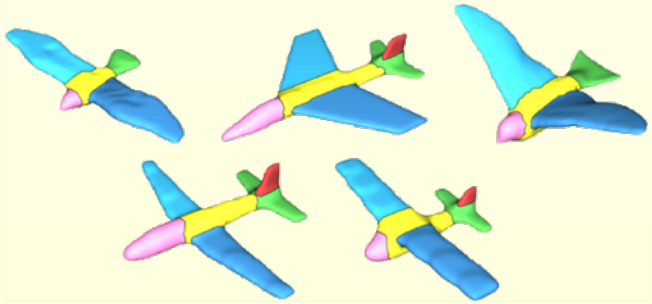
# Shape segmentation and labelling



Anastasia Dubrovina
Computer Science Dept.
Stanford University



Slides credits: E. Kalogerakis, Q. Huang, O. Sidi, R. Hu, L. Yi, N. Mitra, V. Kim

# Motivation - abundance of 3D data

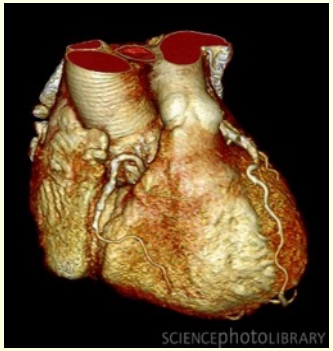

Shape Modeling

Mechanical CAD

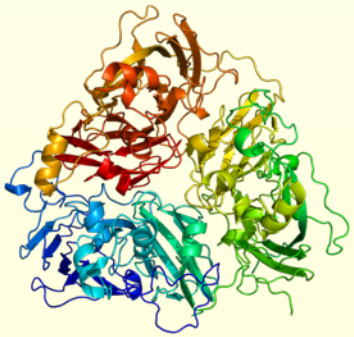
ShapeNet

Buildings

Cultural Heritage



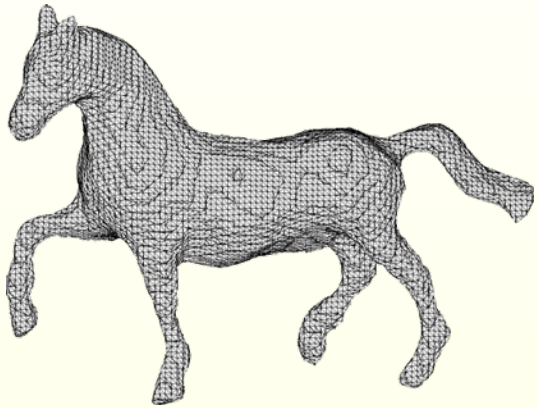

Medicine



Molecular Biology

Slide credit: Q. Huang

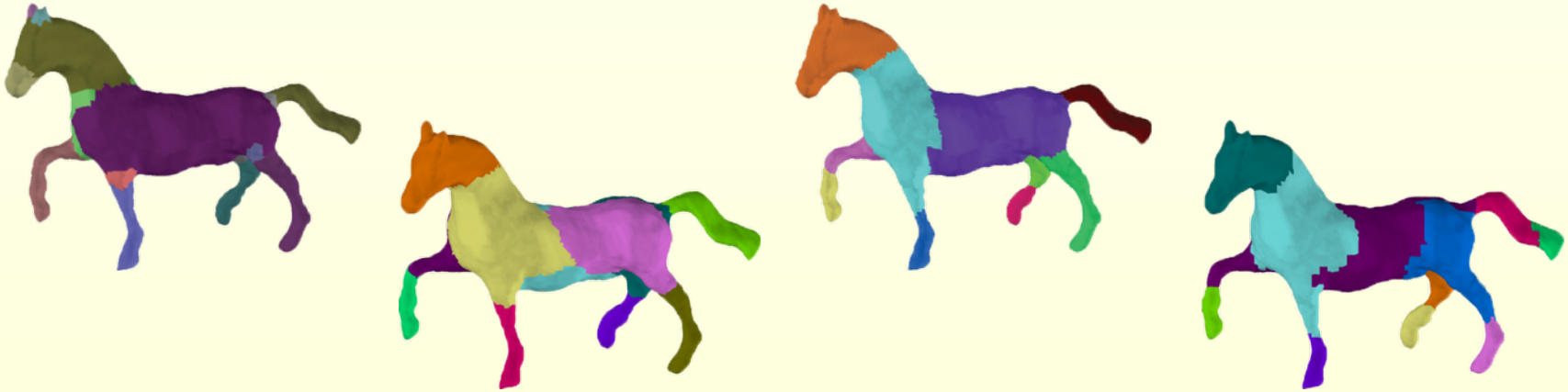
# Shape segmentation / labeling



Input shape

**Segment shape into (semantically) meaningful part**

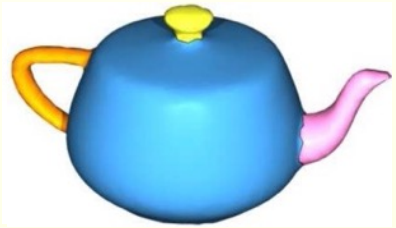
Segmented shape



Kalogerakis et al.'10, Shapira et al.'10, Golovinskiy and Funkhouser'08 (x2), Lai et al.'08

# Importance of shape segmentation

**"How can we decompose a 3D model into parts?"**

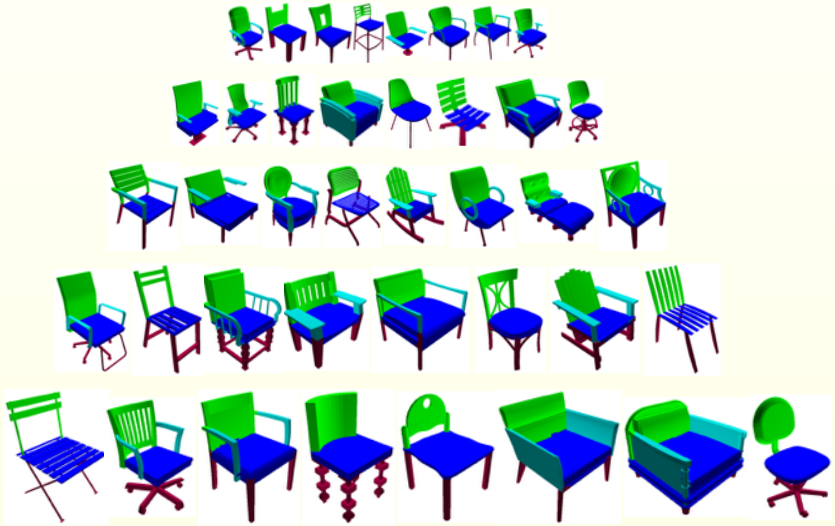


*Psychological research indicates that recognition and shape understanding are based on structural decomposition of the shape into smaller parts [Hoffmann et al. 84,97]*

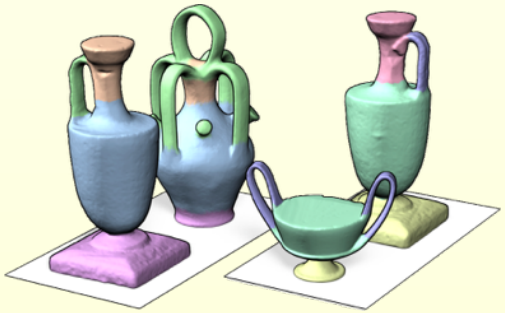
Applications in other shape analysis tasks such as shape matching and shape recognition

Slide credit: Q. Huang

# Applications



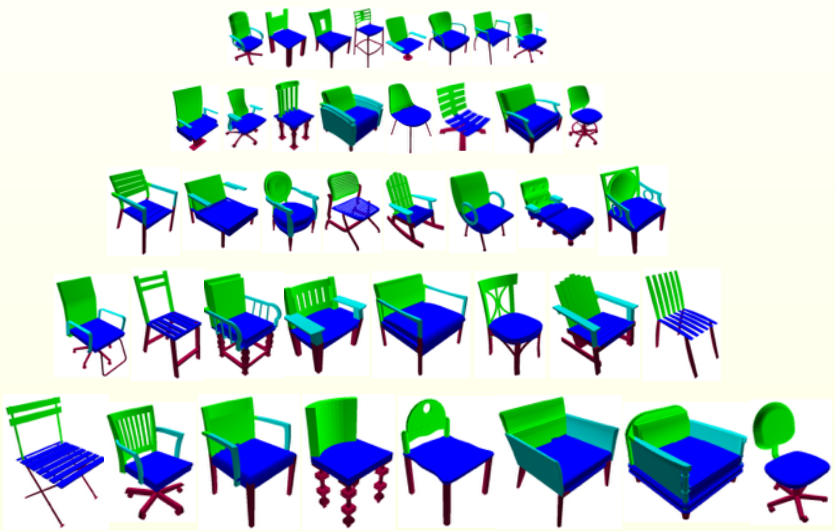
Modeling by example
Funkhouseret al., 2004

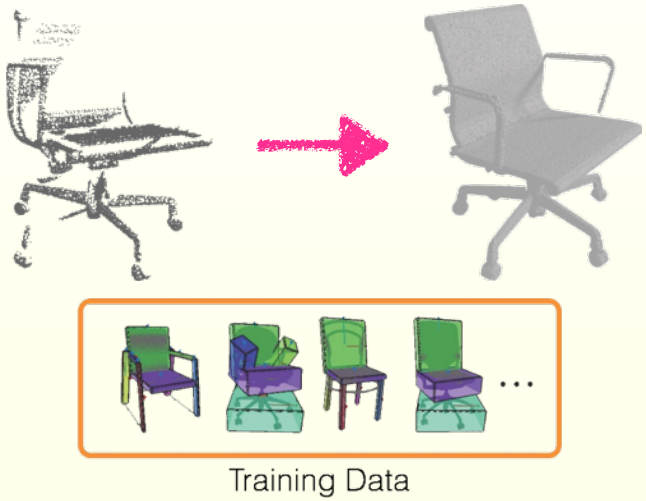


Prior knowledge for part correspondence
van Kaicket al., 2011

Part Based Shape Synthesis
Kalogerakis et al. 2012

# Applications



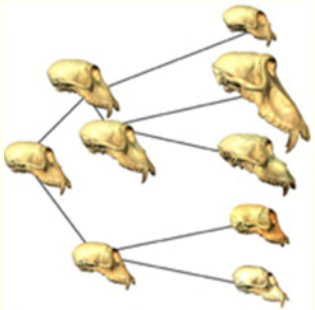



Data-driven shape completion
Sung et al., 2015


Learning to segment new synthetic and scanned shapes
Kalogerakis et al. 2017

Image Based Modeling
Huang et al. 2015

# More applications

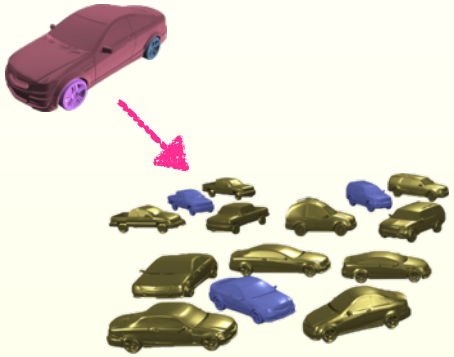


[*Wiley* et al.05]

Paleontology

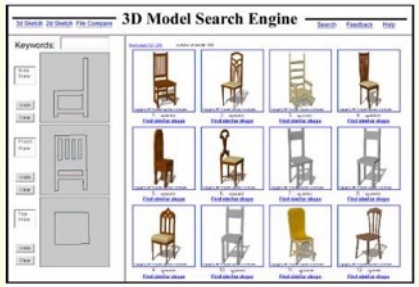

[Cooper et al.10]

Protein folding



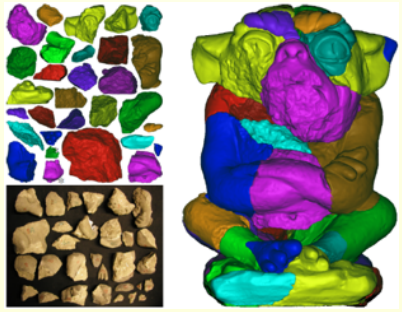
[Yumer and Kara 2014]

Learning custom deformation handles




[Funkhouser et al.05]

Product search



[Huang et al.06]

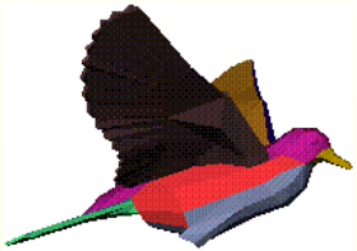
Solving puzzles

Slide credit: Q. Huang

# Lecture outline

- Shape segmentation - problem statement ✓
- Approaches
  - Overview
  - Supervised
    - Learning using co-segmented shape datasets
  - Unsupervised
    - Clustering in descriptor space
  - Semi-supervised
    - Active learning with human in the loop
- Datasets

# Single-shape segmentation: geometry-driven

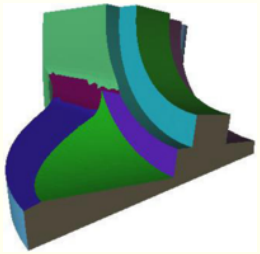


[Shalfman et al. 2002]

K-Means

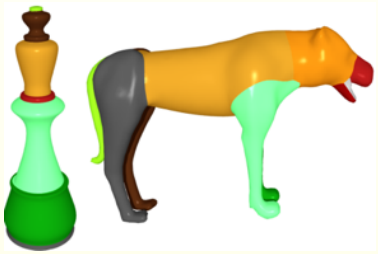
[Katz et al. 05]

Core Extraction



[Attene et. al 2006]

Fitting Primitives



[Lai et al. 08]

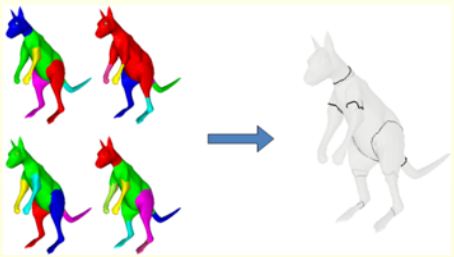
Random Walks

[Golovinskiy and Funkhouser 08]

Normalized Cuts

[Shapira et al. 08]

Shape Diameter Function



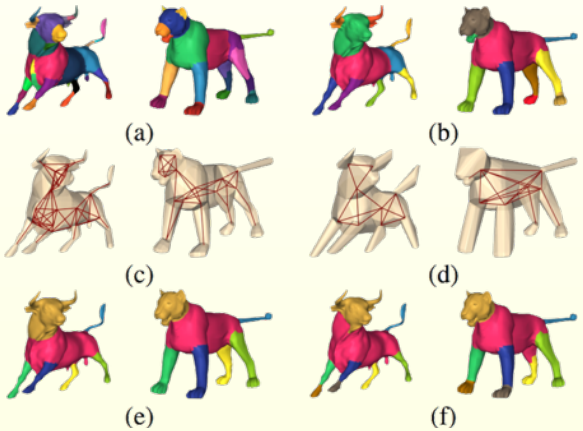
[Golovinskiy and Funkhouser 08]

Randomized Cuts

Slide credit: Q. Huang

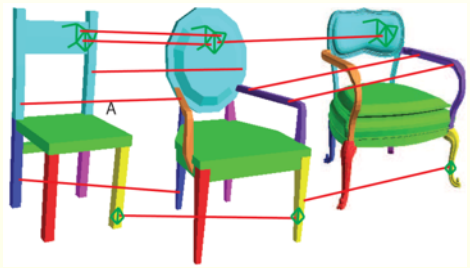
# Consistent segmentation in shape collections

- Can more knowledge be inferred by analyzing a set of shapes?




Kreavoy et al. 2008

Consistent segmentations for model composition



[Golovinskiy and Funkhouser 09]

Consistent segmentations

[Xu el al. 10]

Co-segmentation

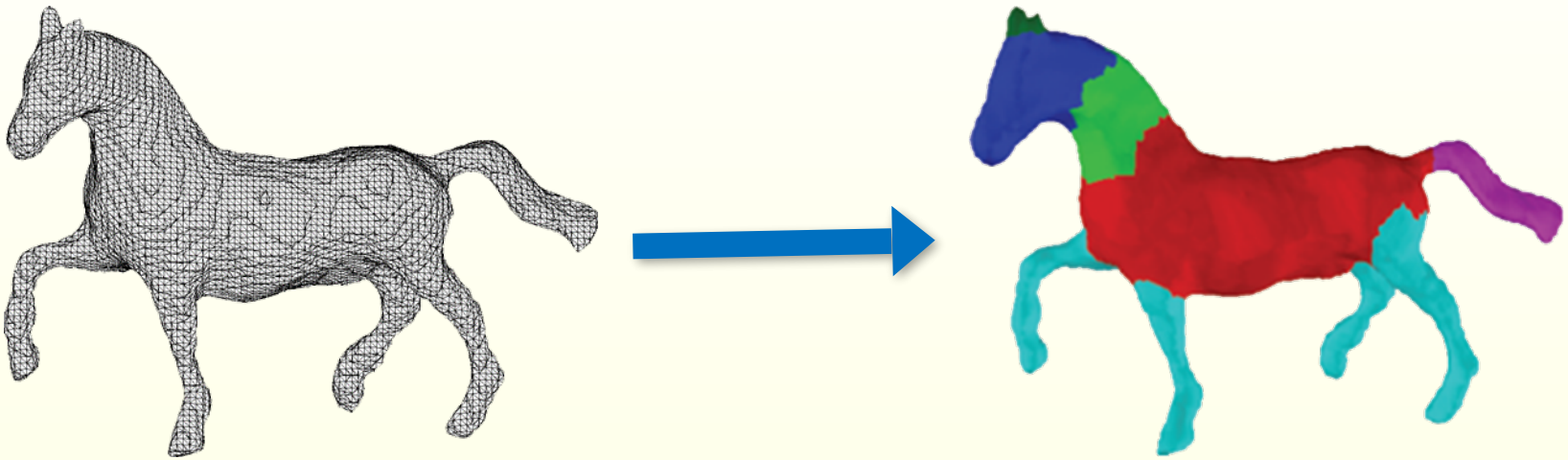
- Explore geometric cues
- Require shapes in correspondence

Slide credit: Q. Huang

Supervised segmentation and labelling

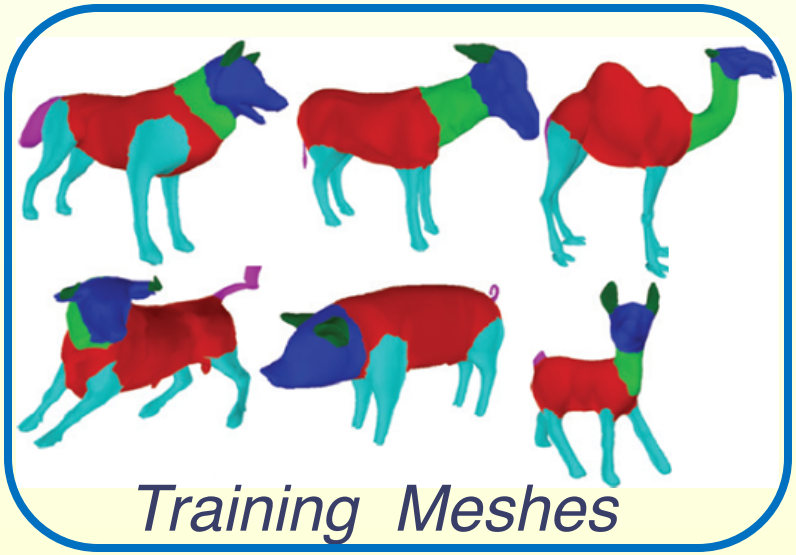
# SUPERVISED SHAPE SEGMENTATION

# Supervised shape segmentation



*Input shape* *Labeled shape*

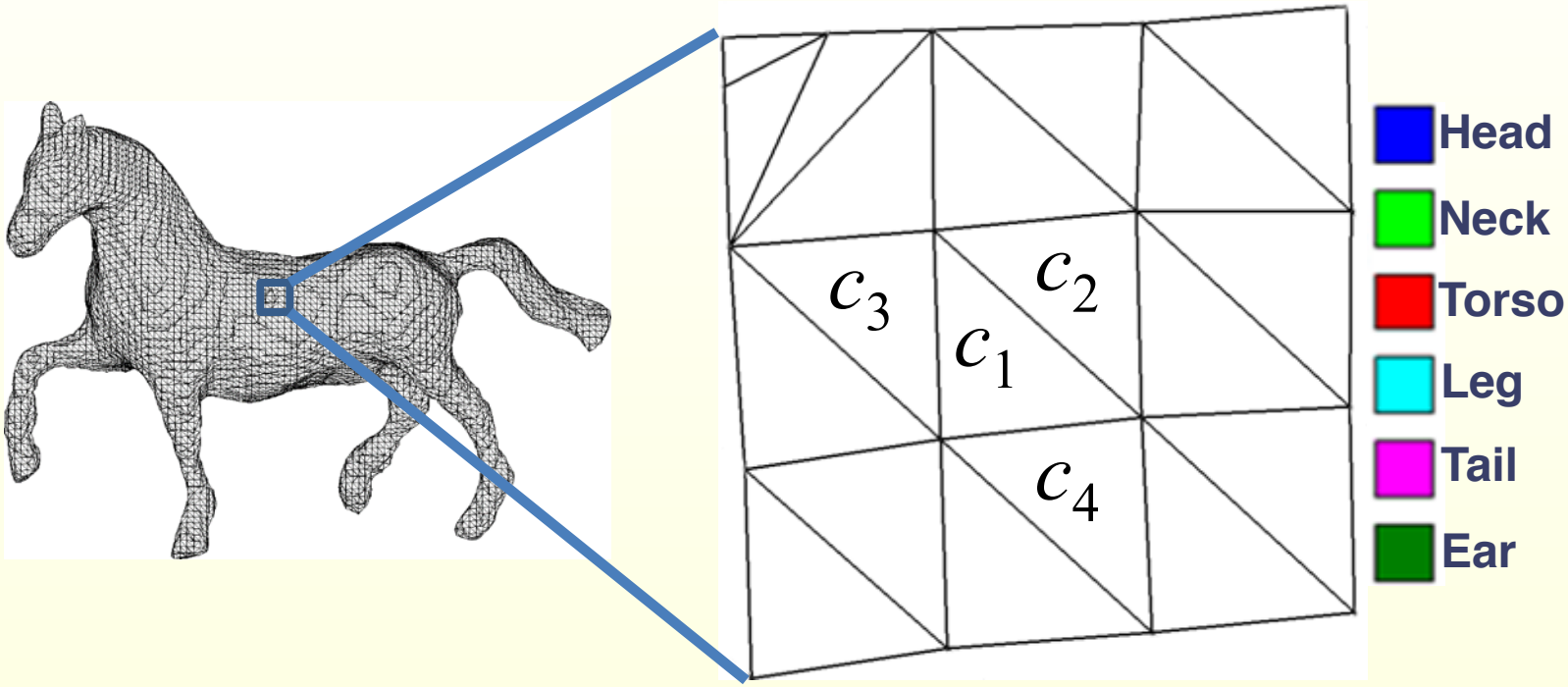
Learn from examples




- Head
- Neck
- Torso
- Leg
- Tail
- Ear

Slide credit: E. Kalogerakis

# Labeling problem statement



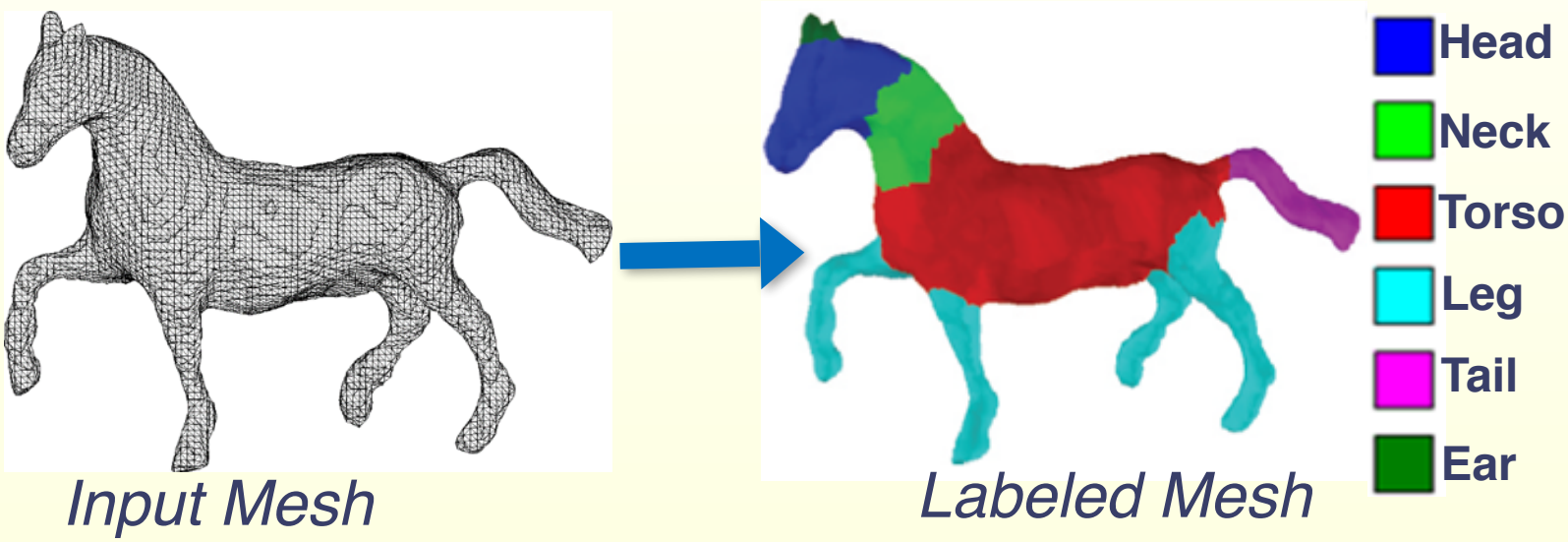

$$c_1, c_2, c_3 \in C$$

$$C = \{ \textit{head}, \textit{neck}, \textit{torso}, \textit{leg}, \textit{tail}, \textit{ear} \}$$

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling

- **"Learning 3D Mesh Segmentation and Labeling"**, [Kalogerakis et al. 2010]

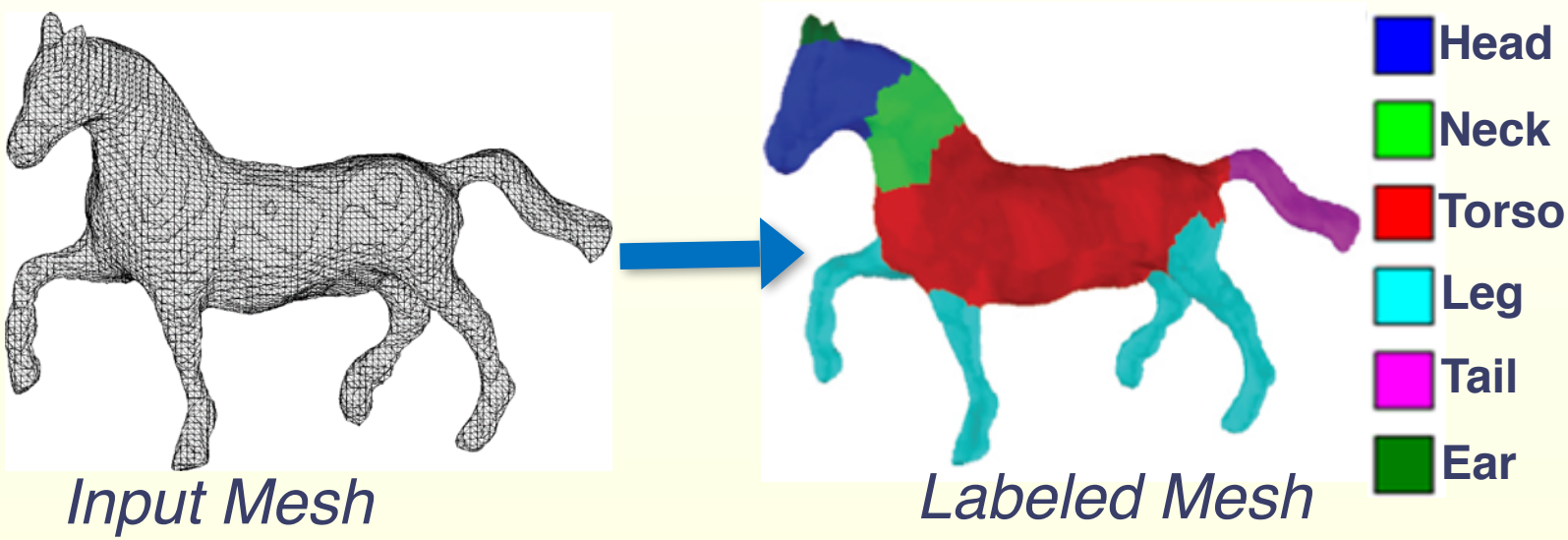



$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \boxed{\mathrm{E}_1(c_i;\mathbf{x_i})} + \sum_{\iota,j} l_{ij} \mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}}) \right\}$$

***Unary term***

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling

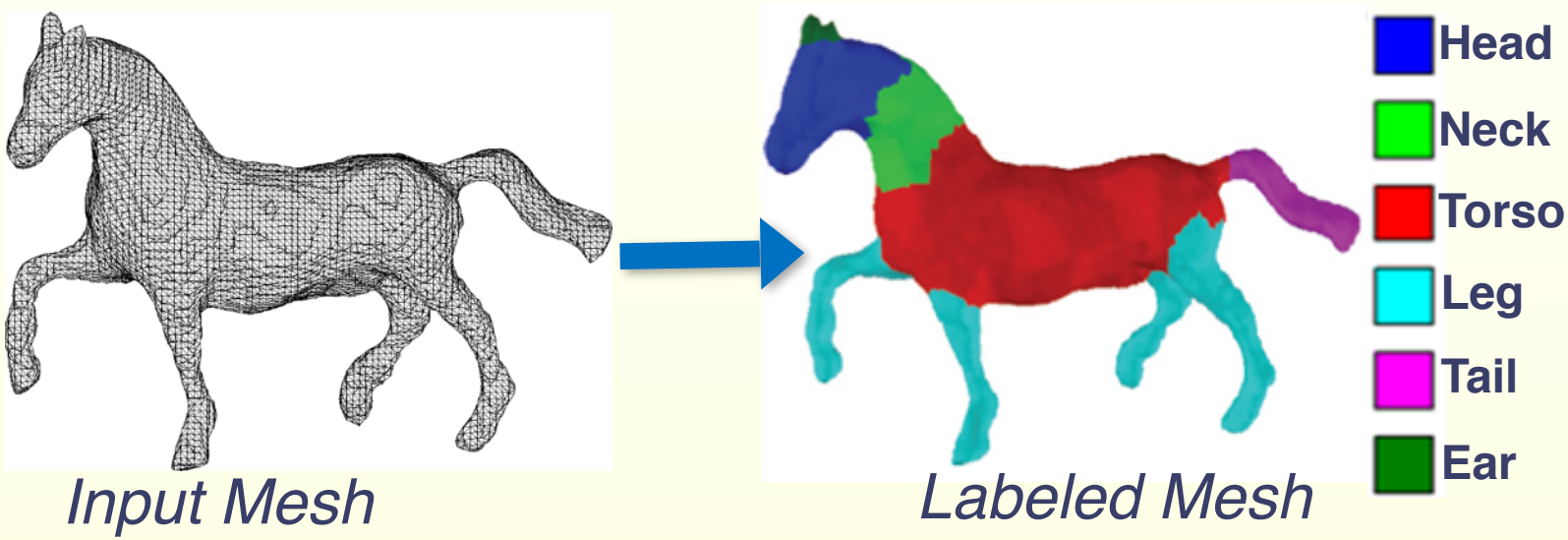



$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} l_{ij} \mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}}) \right\}$$

***Face features***

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling

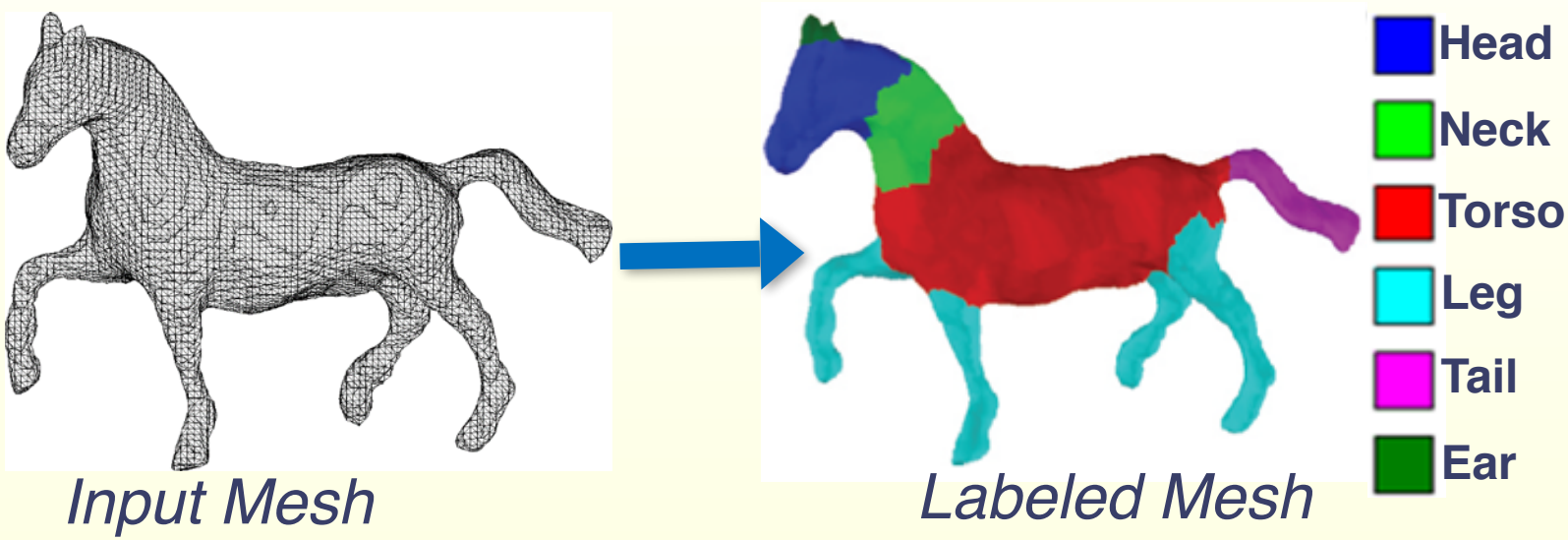



$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} l_{ij} \mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}}) \right\}$$

***Face Area***

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling

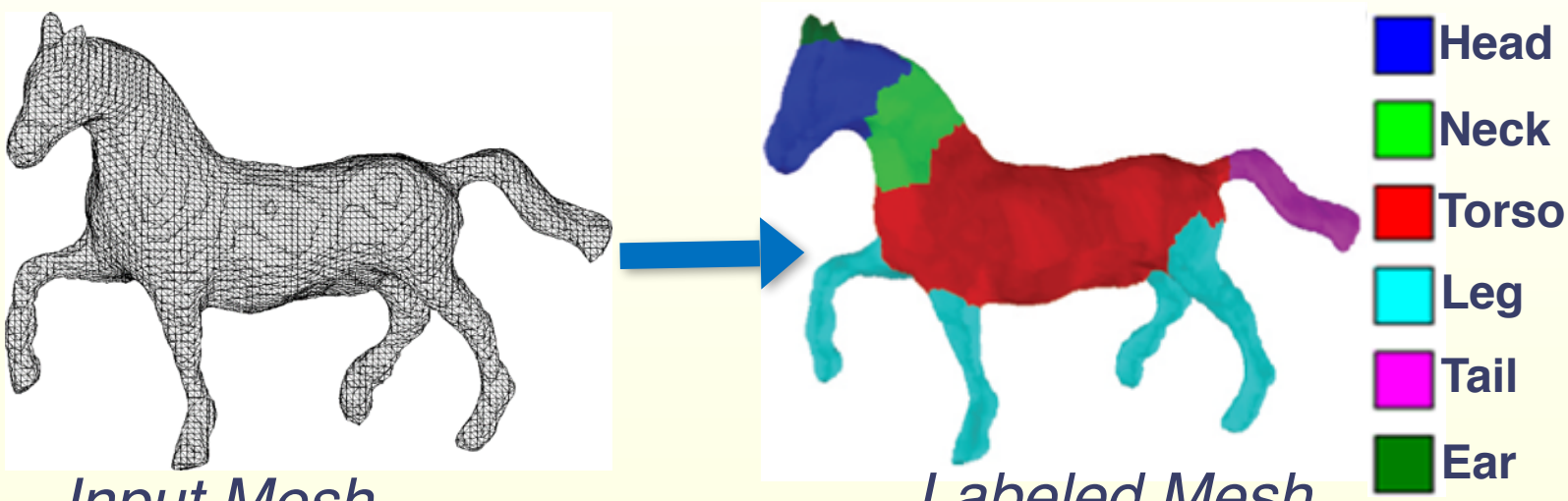



$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} l_{ij} \boxed{\mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}})} \right\}$$

***Pairwise Term***

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling



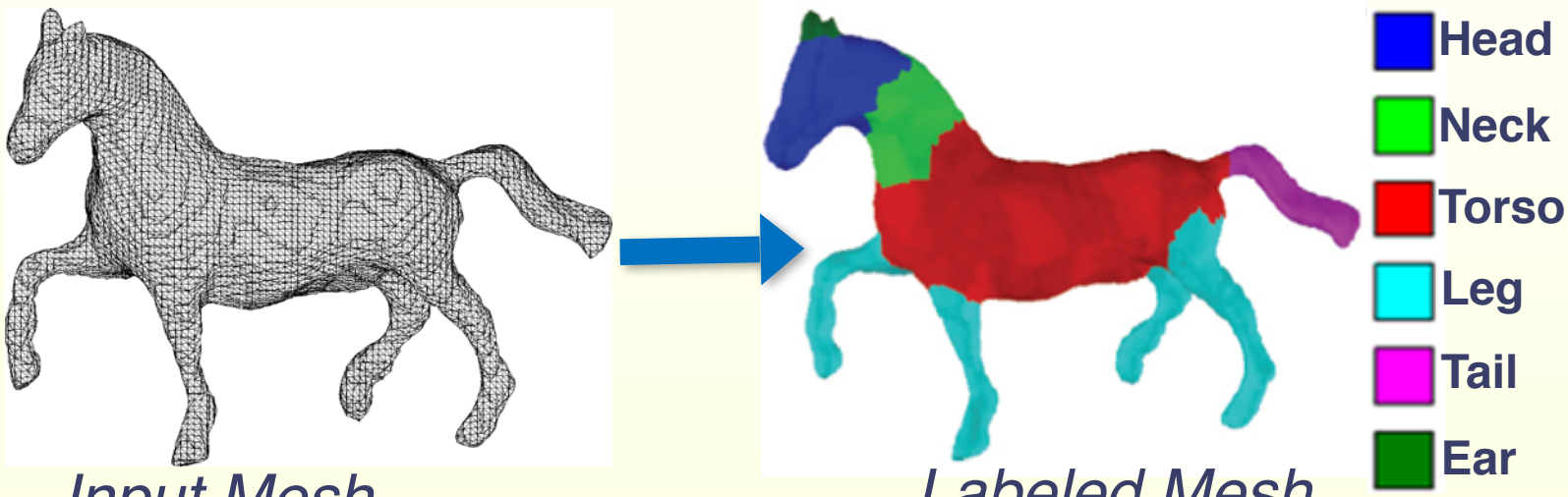

*Input Mesh* *Labeled Mesh*

$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} l_{ij} \mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}}) \right\}$$

***Edge Features***

Slide credit: E. Kalogerakis

# Conditional Random Field for Labeling




*Input Mesh* *Labeled Mesh*

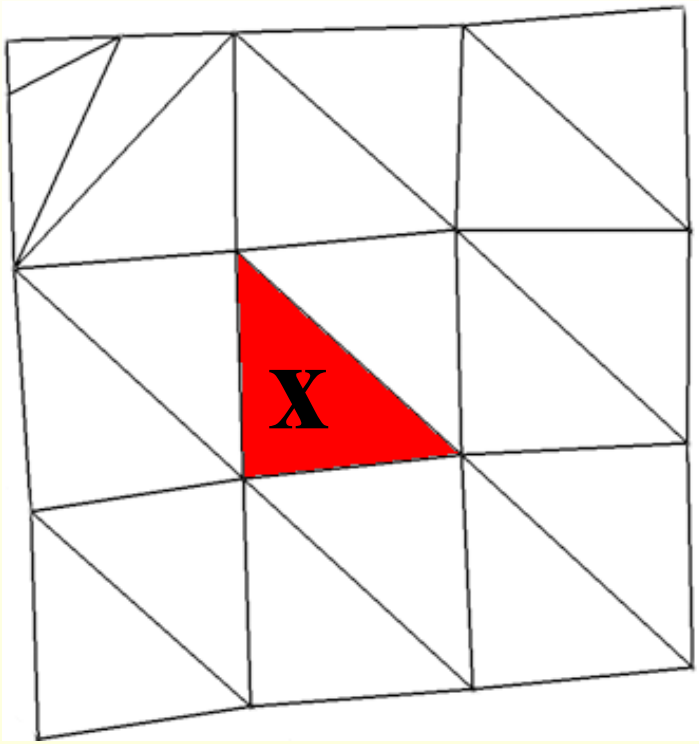
$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} \boxed{l_{ij}} \mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}}) \right\}$$

***Edge Length***

Slide credit: E. Kalogerakis

# Feature vector

$$\mathbf{x} \in \Re^{375+35|C|} \rightarrow \mathrm{P}(c \mid \mathbf{x})$$



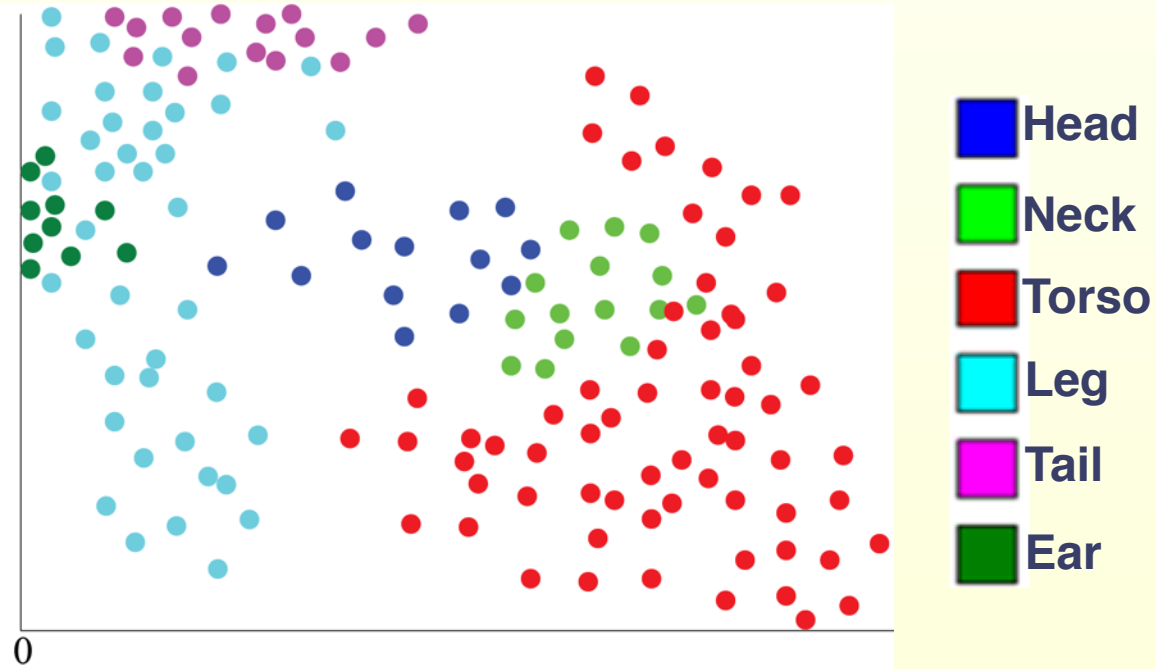

- surface curvature
- singular values from PCA
- shape diameter
- distances from medial surface
- average geodesic distances
- shape contexts
- spin images
- contextual label features

Using more features helps

Slide credit: E. Kalogerakis

# Learning a classifier

$$\rightarrow \{(\mathbf{x}_i, c_i)\}$$

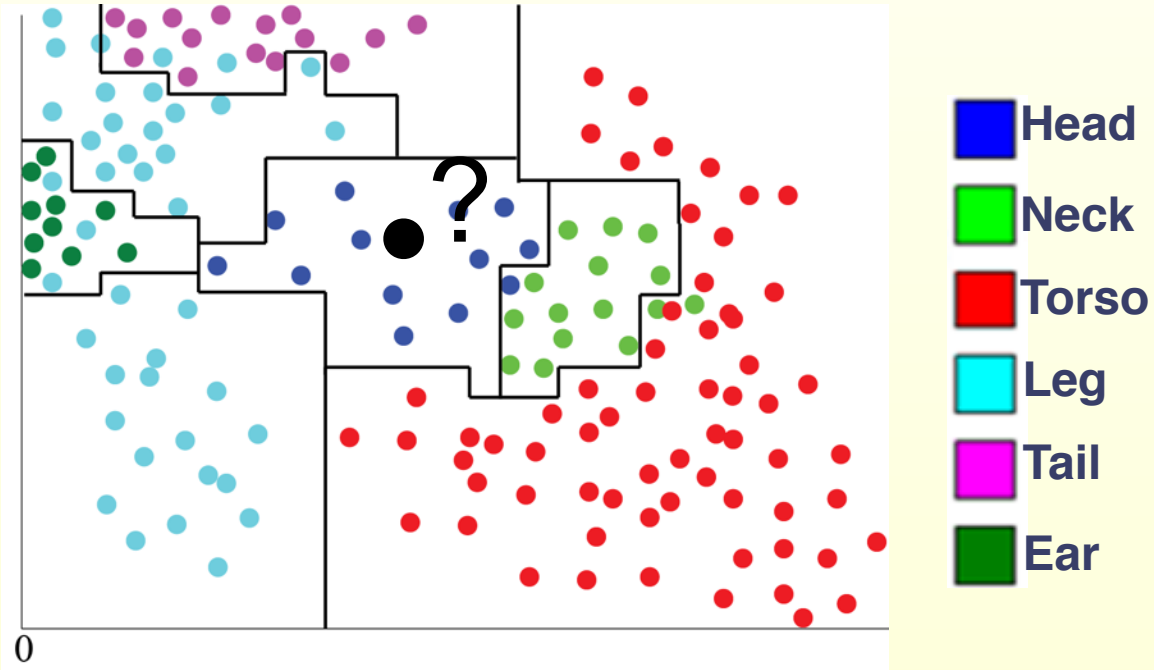



Slide credit: E. Kalogerakis

# Learning a classifier

We use  sifier [Torralba et al. 2007]

$\rightarrow \{(\mathbf{x}_i, c_i)\}$




Slide credit: E. Kalogerakis

# Joint-Boost classifier [Torralba et al. 2007]

- Properties
  - Automatic feature selection

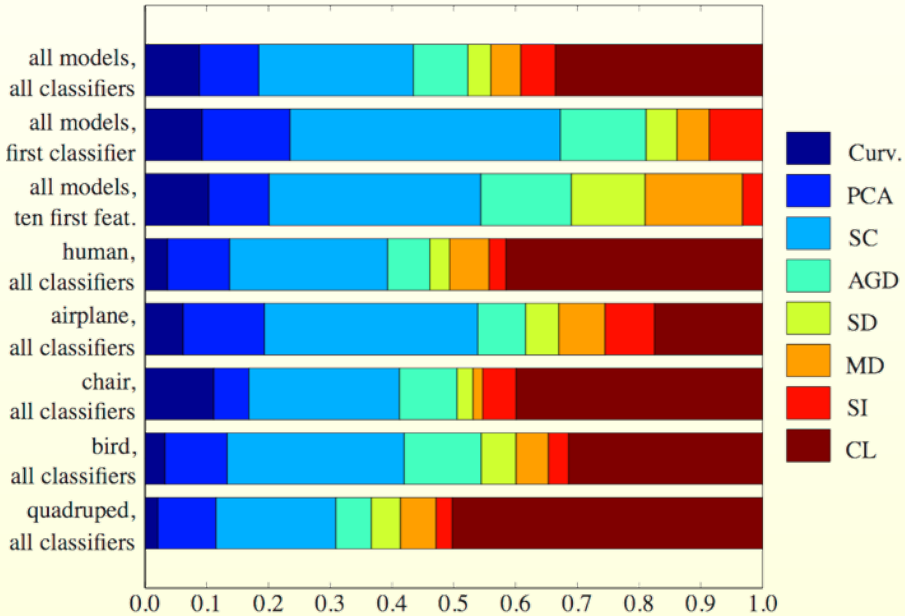



**Figure 5:** *Percentages of features used by JointBoost for different cases. See text for details. Legend: Curv.=curvature, PCA=PCA singular values, SC=shape contexts, AGD=average geodesic distances, SD=shape dimeter, MD=distance from medial surface, SI = Spin Images, CL = contextual label features.*

Slide credit: E. Kalogerakis

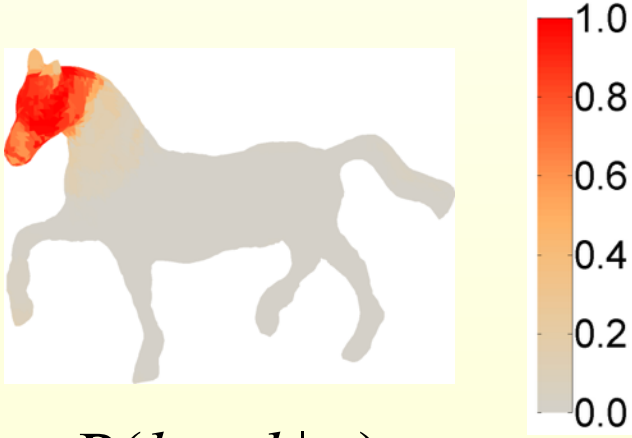
# Joint-Boost classifier [Torralba et al. 2007]

- Properties
  - Automatic feature selection
  - Can handle large number of input features
  - Fast sequential learning algorithm
  - Shares features among classes
  - Produces output probabilities

$$\mathbf{z} \longrightarrow P(c = l|\mathbf{z})$$

feature vector

probability for each class label $l$




$\mathrm{P}(head \mid \mathbf{x})$

Slide credit: E. Kalogerakis

# Joint-Boost classifier [Torralba et al. 2007]

- Algorithm outline
  - Classifier composed of *decision stumps*

$$h(\mathbf{z}, l; \phi) = \begin{cases} a & z_f > \tau \text{ and } l \in \boxed{\mathcal{C}_S} \\ b & z_f \leq \tau \text{ and } l \in \mathcal{C}_S \\ k_l & l \notin \mathcal{C}_S \end{cases}$$

Set of classes

Algorithm parameters $\phi$ : $f, a, b, \tau$, the set $\mathcal{C}_S$, and $k_l$

Slide credit: E. Kalogerakis

# Joint-Boost classifier [Torralba et al. 2007]

- Algorithm outline
  - Classifier composed of *decision stumps*

$$h(\mathbf{z}, l; \phi) = \begin{cases} a & z_f > \tau \text{ and } l \in \mathcal{C}_S \\ b & z_f \leq \tau \text{ and } l \in \mathcal{C}_S \\ k_l & l \notin \mathcal{C}_S \end{cases}$$

  - Scores class labels by thresholding $f$-th entry of a feature vector $\mathbf{z}$
  - Probability of a given class $l$

$$H(\mathbf{z}, l) = \sum_j h(\mathbf{z}, l; \phi_j)$$

All parameters

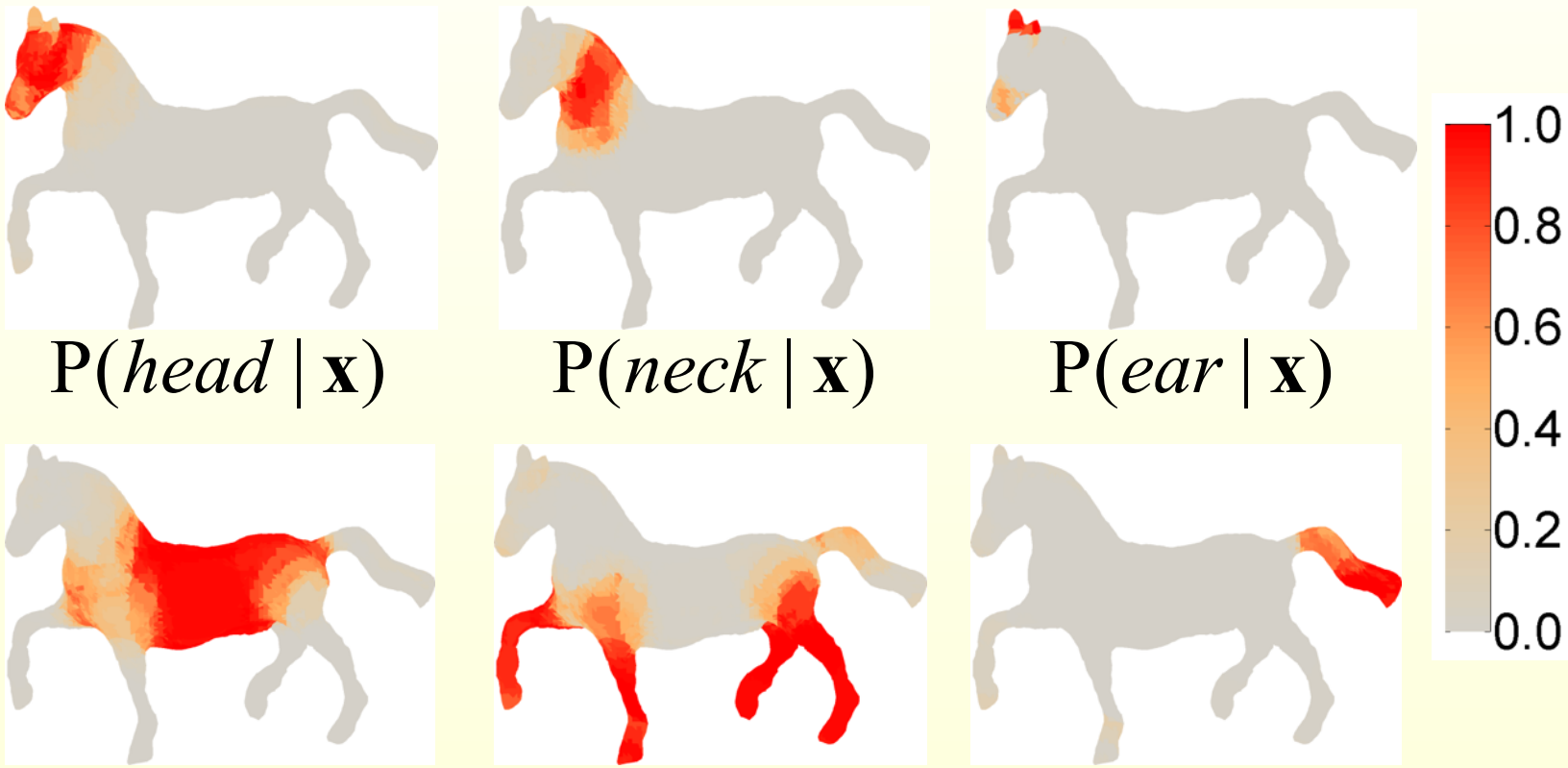
$$P(c = l | \mathbf{z}, \xi) = \frac{\exp(H(\mathbf{z}, l))}{\sum_{\ell \in \mathcal{C}} \exp(H(\mathbf{z}, \ell))}$$

Soft-max

Slide credit: E. Kalogerakis

# Labeling energy: unary term

$$E_1(c;\mathbf{x}) = -\log P(c \mid \mathbf{x})$$

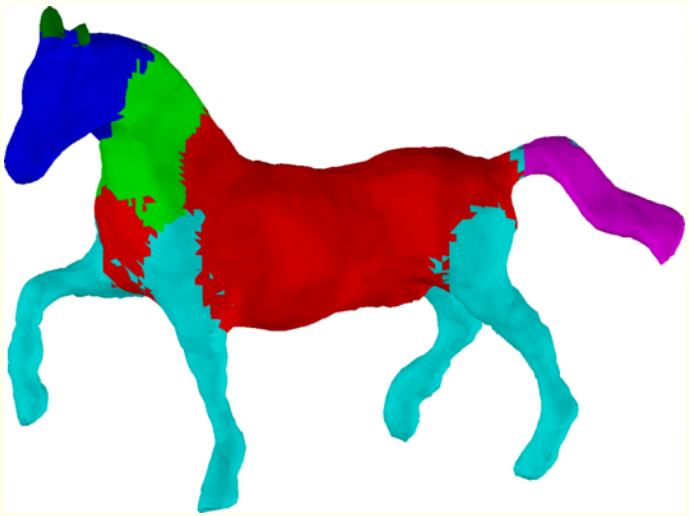



$P(head \mid \mathbf{x})$ $P(neck \mid \mathbf{x})$ $P(ear \mid \mathbf{x})$

$P(torso \mid \mathbf{x})$ $P(leg \mid \mathbf{x})$ $P(tail \mid \mathbf{x})$

Slide credit: E. Kalogerakis

# Labeling using unary term alone

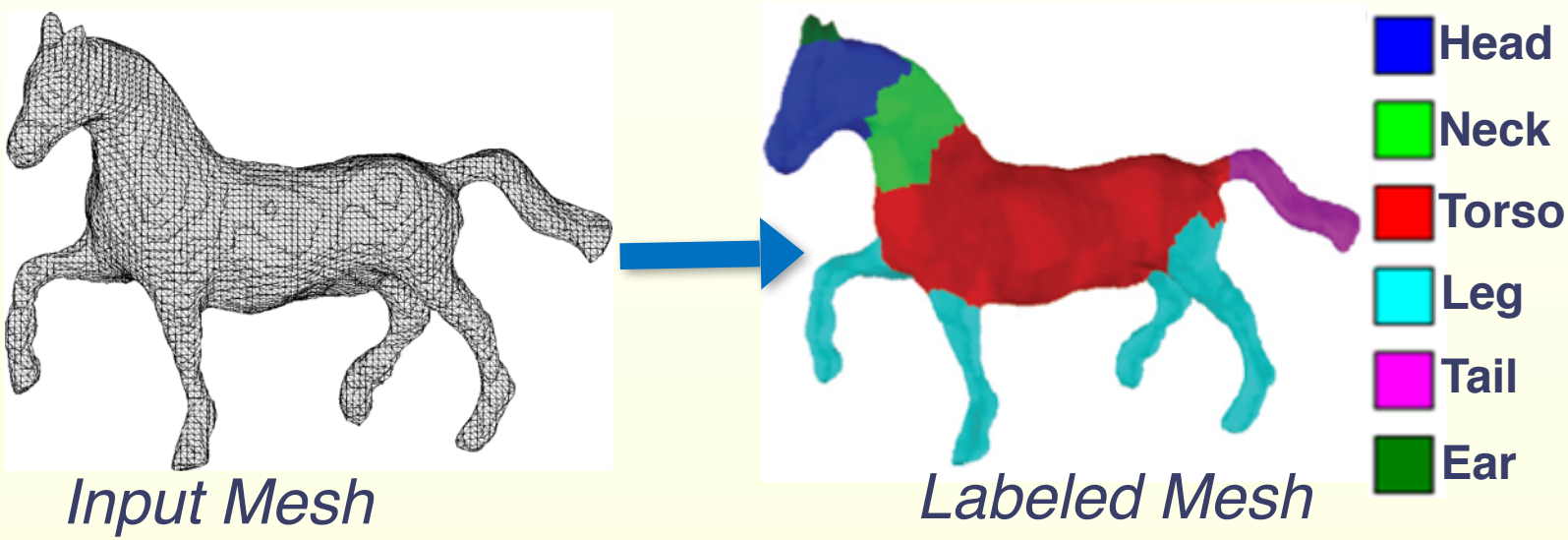


$$\arg\max_{c} P(c \mid \mathbf{x})$$

*Most-likely labels*

Slide credit: E. Kalogerakis

# Conditional random field labeling




$$c^* = \arg\min_{\mathbf{c}} \left\{ \sum_{\iota} \alpha_i \mathrm{E}_1(c_i; \mathbf{x_i}) + \sum_{\iota, j} l_{ij} \boxed{\mathrm{E}_2(c_i, c_j; \mathbf{y_{ij}})} \right\}$$

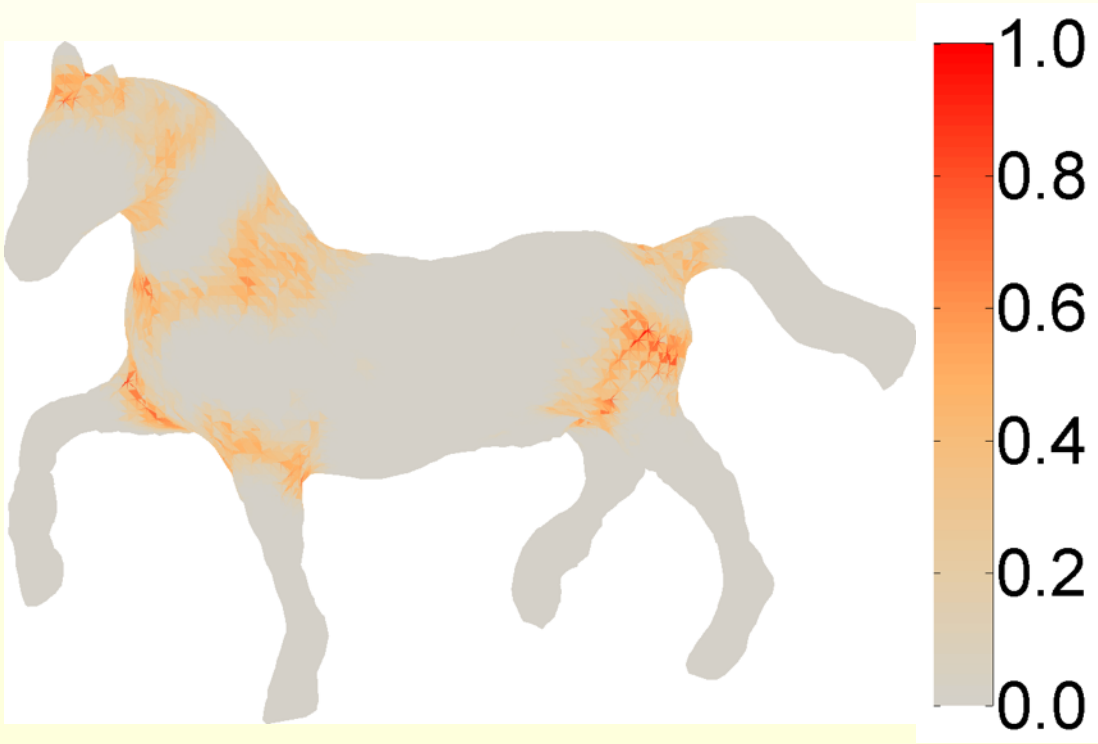
***Pairwise Term***

Slide credit: E. Kalogerakis

# Pairwise Term

$$\mathrm{E}_2(c,c';\mathbf{y},\theta_2) = \boxed{G(\mathbf{y})}L(c,c')$$

***Geometry-dependent term: likelihood of label change based on geometry alone***




Slide credit: E. Kalogerakis

# Pairwise Term

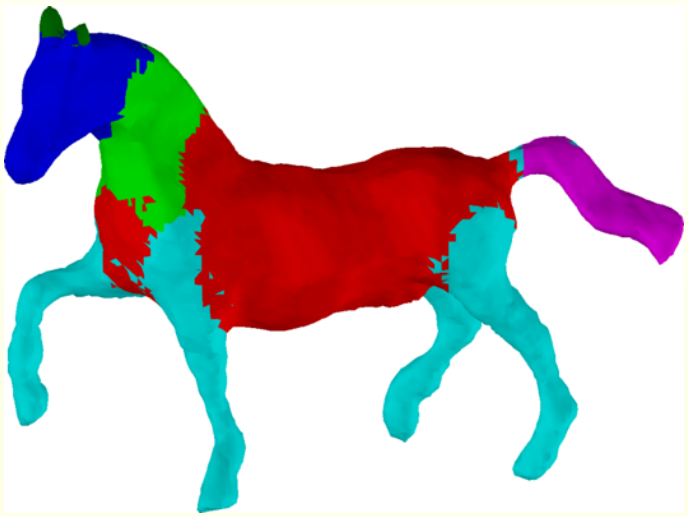
$$E_2(c,c';\mathbf{y},\theta_2) = G(\mathbf{y})\boxed{L(c,c')}$$

***Learned label compatibility term: learned with JointBoost from geometric 191-D features***

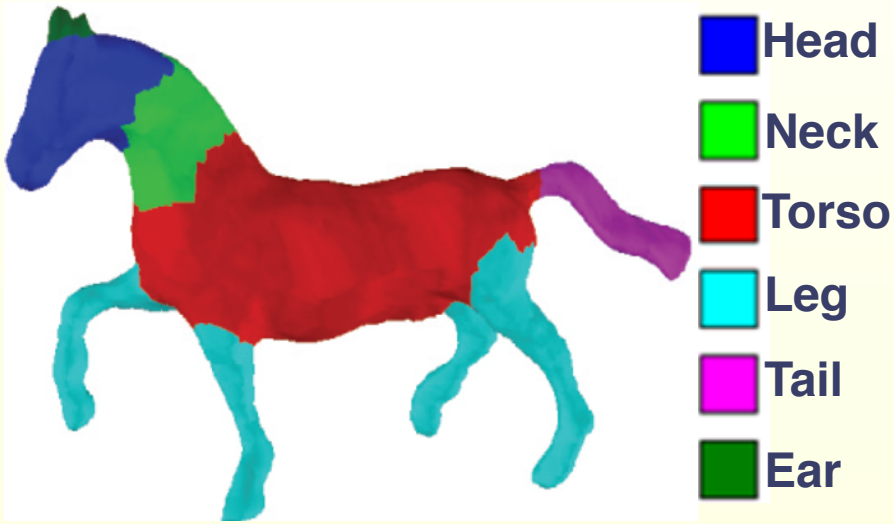
$$L(c,c') = \begin{array}{c} \begin{array}{cccccc} \textbf{Head} & \textbf{Neck} & \textbf{Ear} & \textbf{Torso} & \textbf{Leg} & \textbf{Tail} \end{array} \\ \begin{bmatrix} 0 & .45 & .07 & 1 & \infty & \infty \\ .45 & 0 & \infty & 1 & \infty & \infty \\ .07 & \infty & 0 & \infty & \infty & \infty \\ 1 & 1 & \infty & 0 & 1 & .56 \\ \infty & \infty & \infty & 1 & 0 & \infty \\ \infty & \infty & \infty & .56 & \infty & 0 \end{bmatrix} \end{array} \begin{array}{l} \\ \textbf{Head} \\ \textbf{Neck} \\ \textbf{Ear} \\ \textbf{Torso} \\ \textbf{Leg} \\ \textbf{Tail} \end{array}$$

Slide credit: E. Kalogerakis

# Full CRF result



*Unary term classifier*




*Full CRF result*

Slide credit: E. Kalogerakis

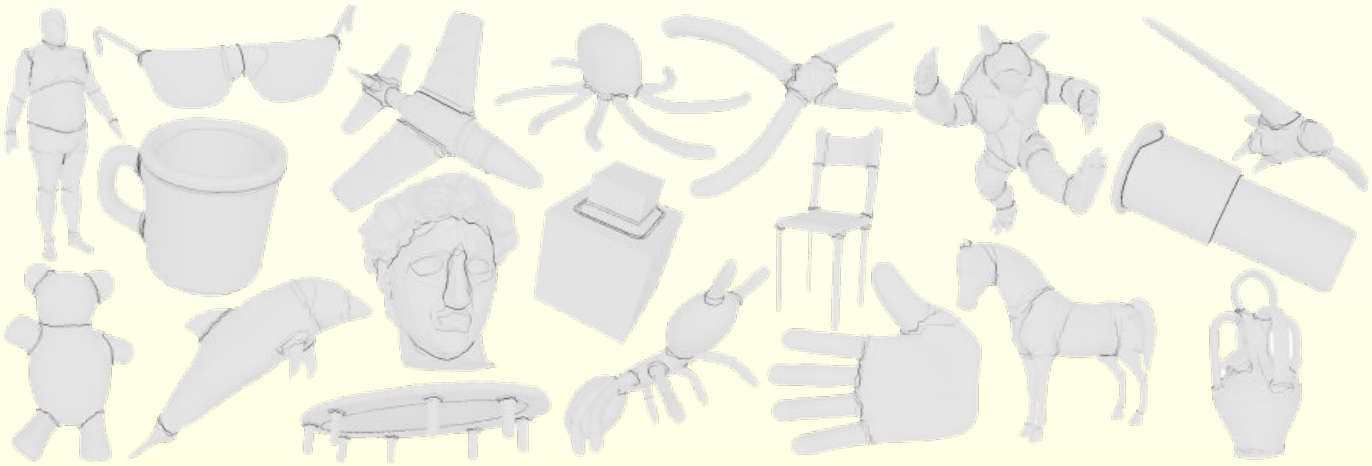
# Learning and inference

- Learn unary classifier and $G(y)$ with Joint Boosting [Torralba et al. 2007]
- Hold-out validation for the rest of parameters
- CRF inference - using graph cuts [Boykov et al. 2001]

Slide credit: E. Kalogerakis

# Dataset used in experiments

- Princeton Segmentation Benchmark (PSB) [Chen et al. 2009]
  http://segeval.cs.princeton.edu

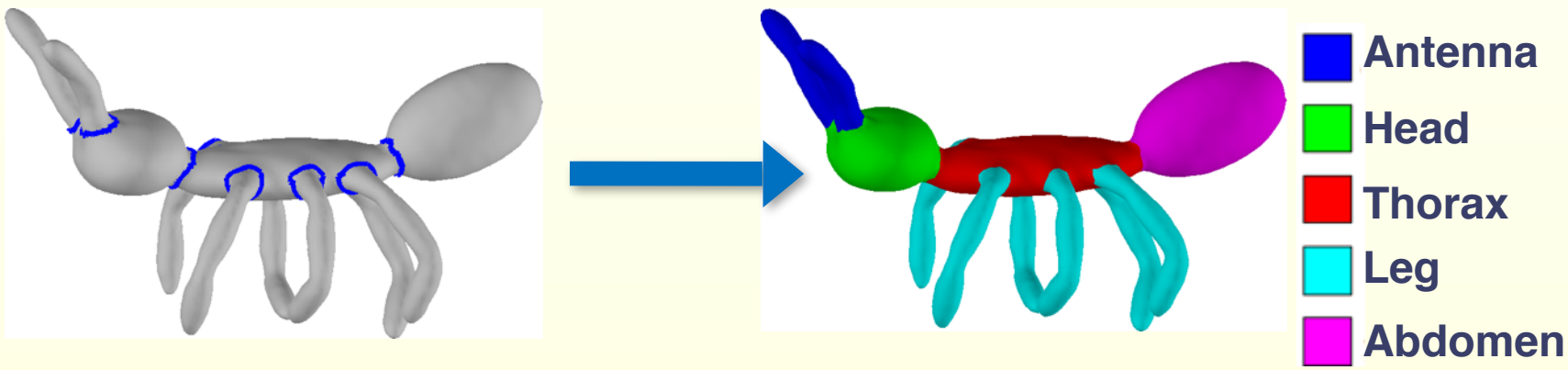


- 11 human generated segmentations (“probabilistic” ground truth)
  - 380 watertight meshes across 19 categories

Slide credit: E. Kalogerakis

# Dataset used in experiments

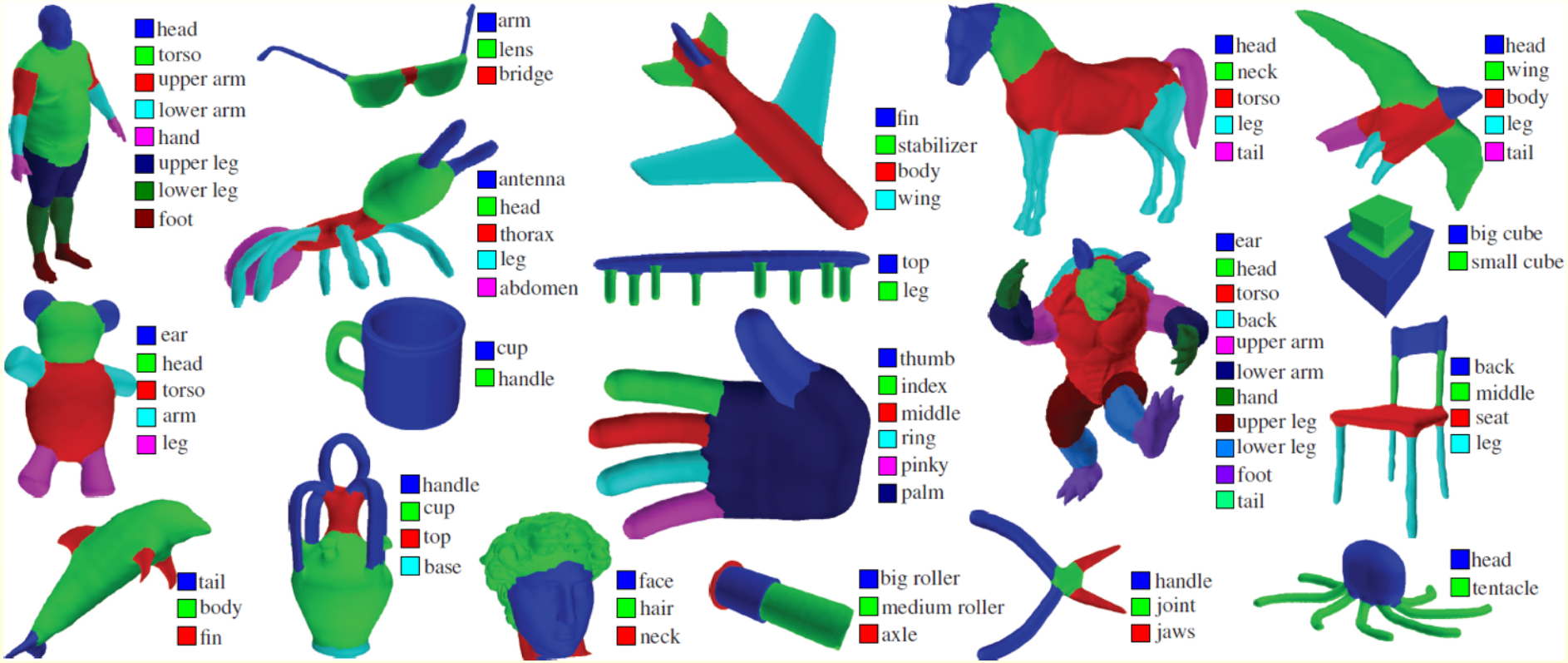
- We label 380 meshes from the PCB [Chen *et al.* 2009]




- Each of the 19 categories is treated separately

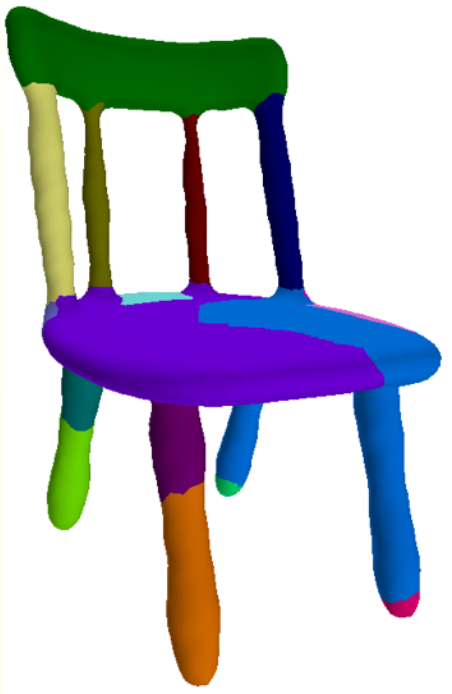
Slide credit: E. Kalogerakis

# Labeling results

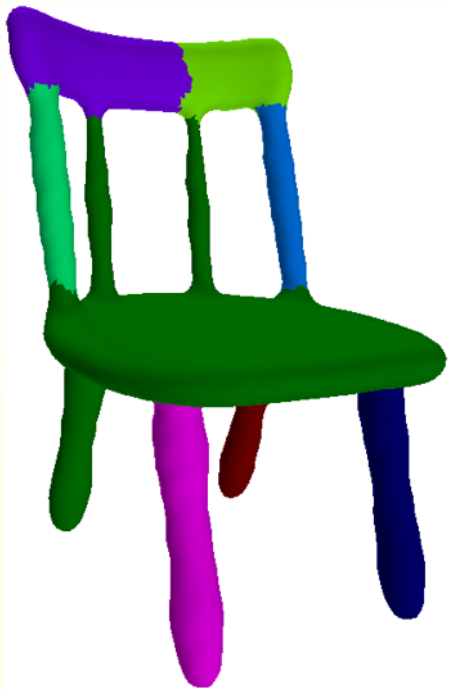



Slide credit: E. Kalogerakis

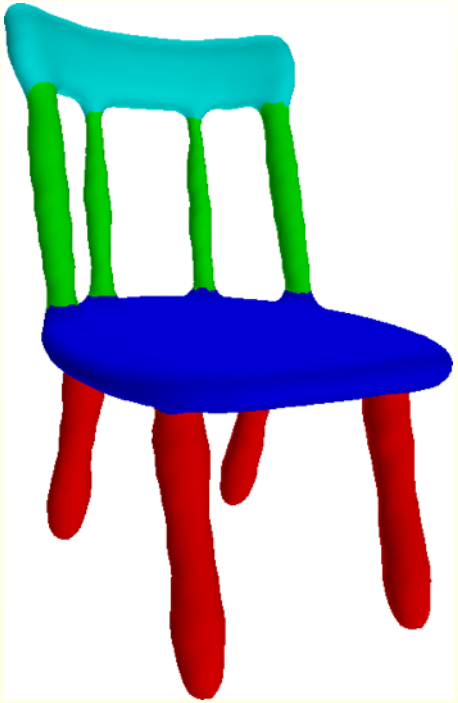
# Segmentation Comparisons



**Shape Diameter [Shapira et al. 10]**



**Randomized Cuts [Golovinskiy and Funkhouser 08]**



**Our approach**

Slide credit: E. Kalogerakis

# Segmentation Comparisons

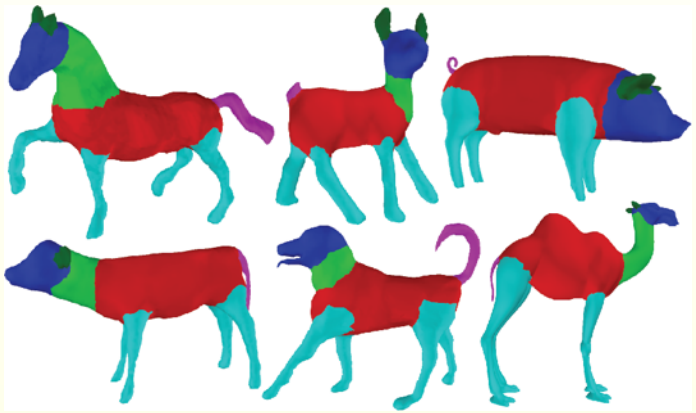
**Shape Diameter [Shapira et al. 10]**

**Randomized Cuts [Golovinskiy and Funkhouser 08]**

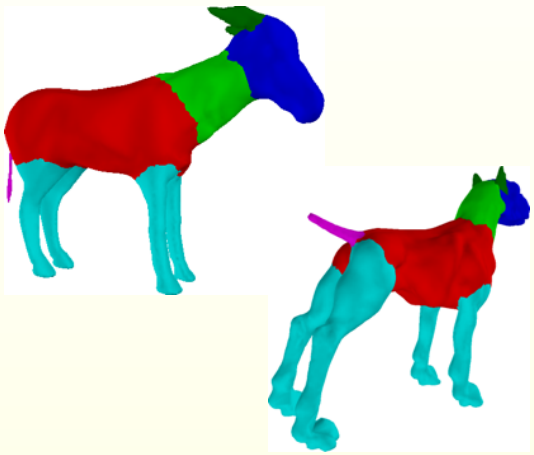
**Our approach**

Slide credit: E. Kalogerakis

# Learning different segmentation styles

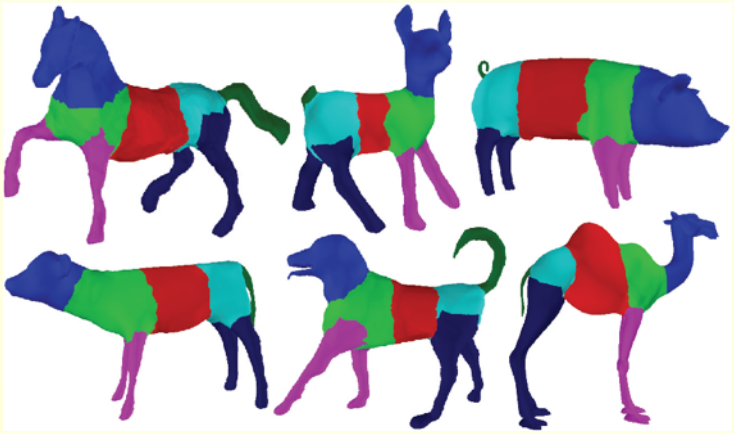


Head
Neck
Torso
Leg
Tail
Ear

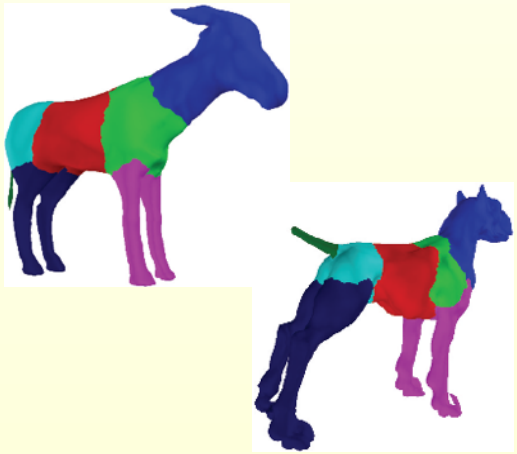


*Training Meshes*

*Test Meshes*

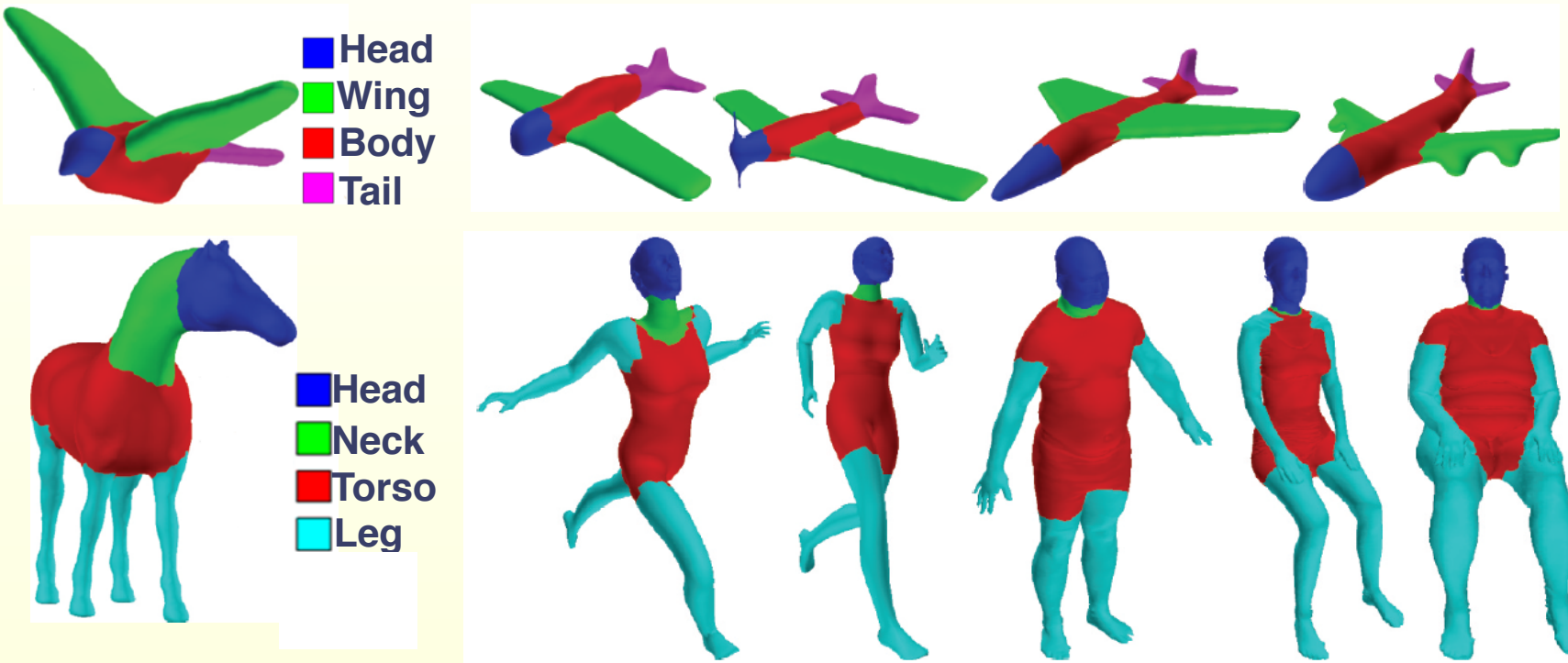


Head
Front Torso
Middle Torso
Back Torso
Front Leg
Back Leg
Tail



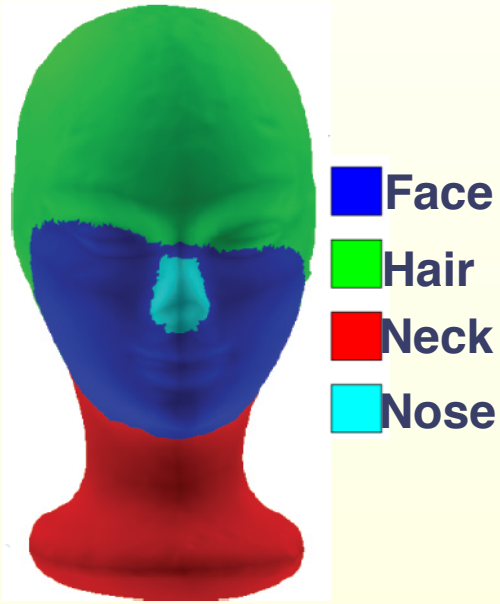
Slide credit: E. Kalogerakis

# Generalization to different categories

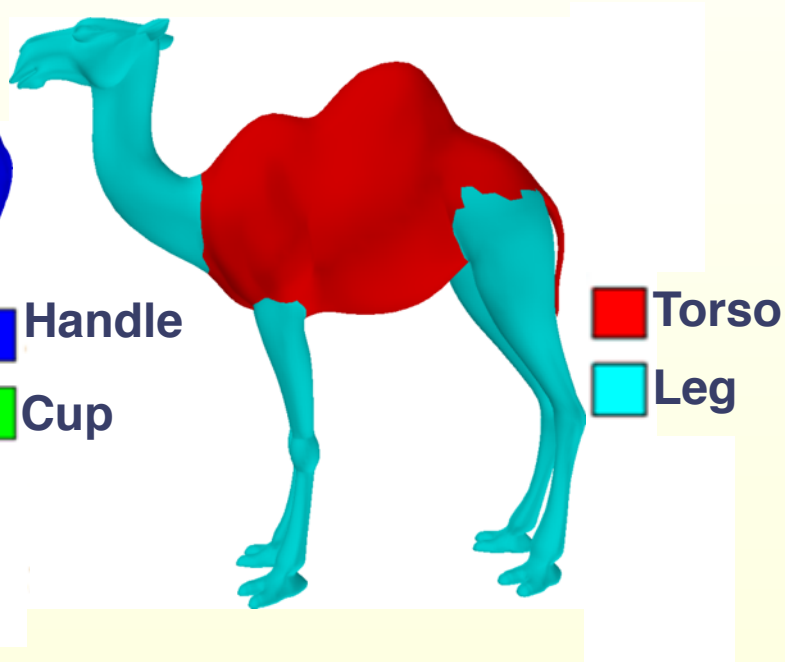



Slide credit: E. Kalogerakis

# Failure cases





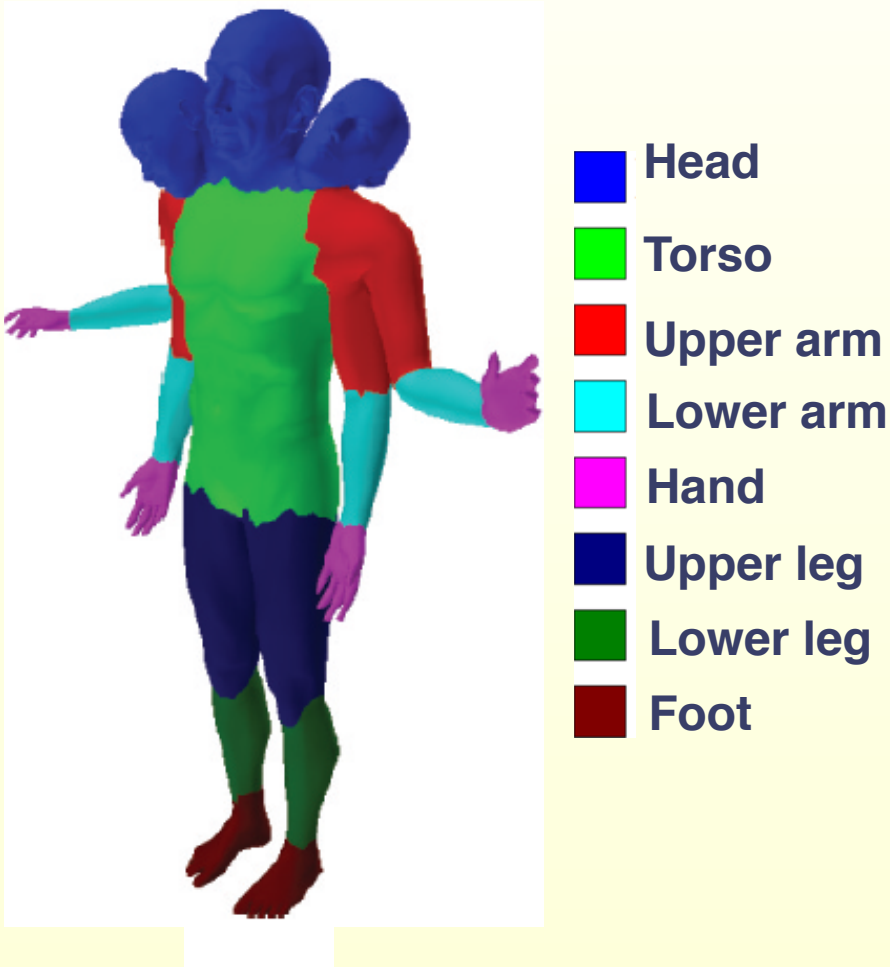



Slide credit: E. Kalogerakis

# Limitations (common to most approaches)

- Adjacent segments with the same label are merged

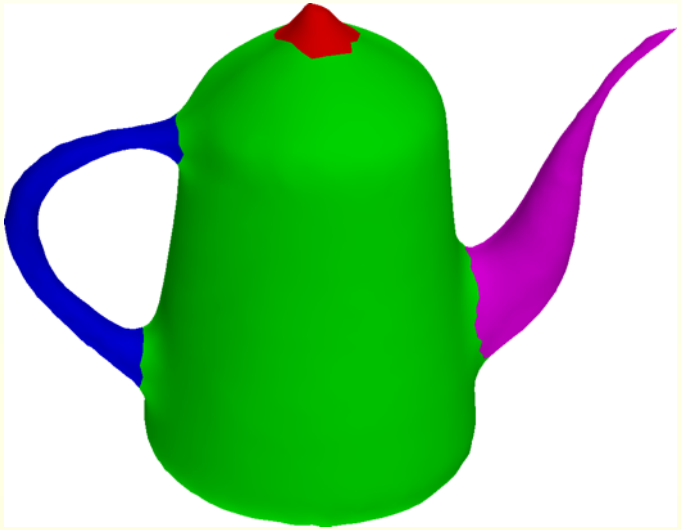
Can't do part instance segmentation



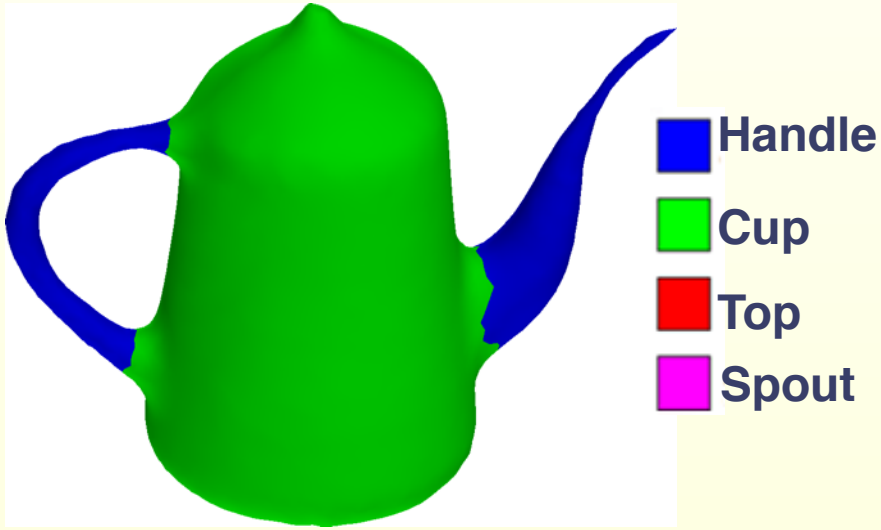

Slide credit: E. Kalogerakis

# Limitations

- Results depend on having sufficient training data



*19 training meshes*

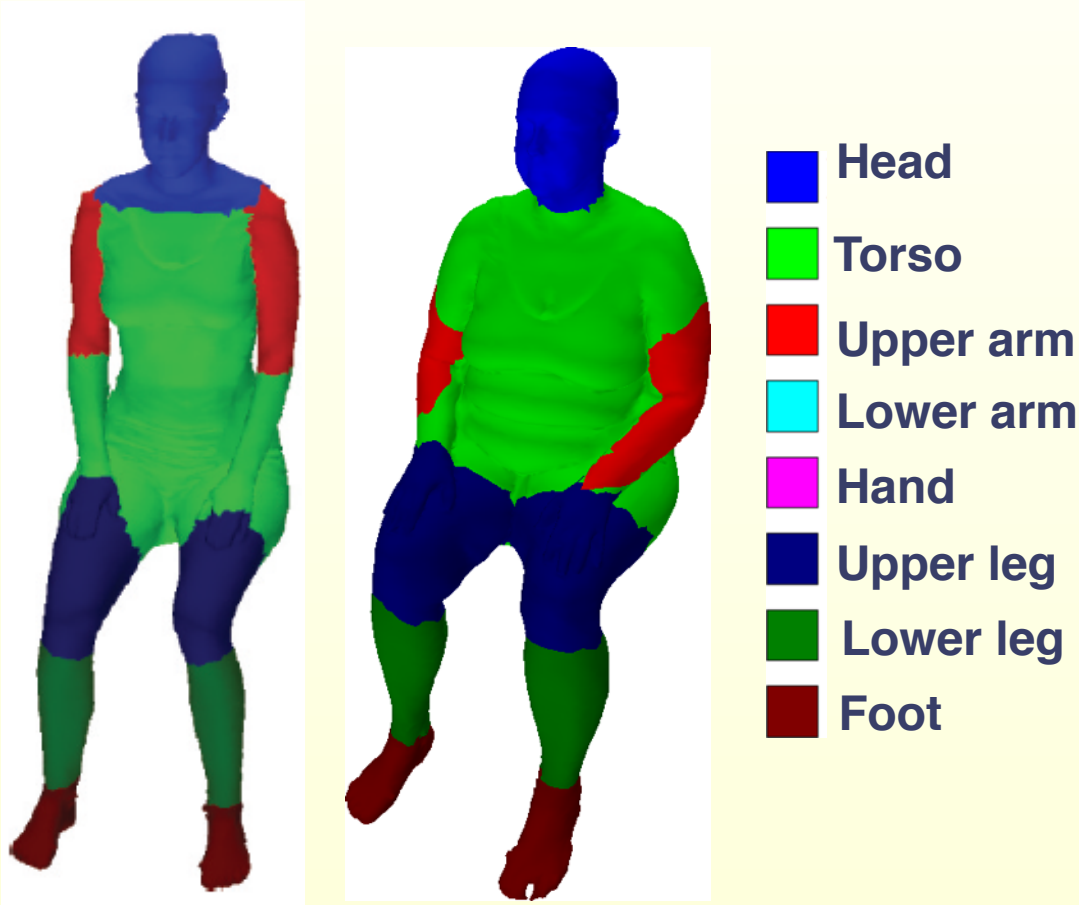



*3 training meshes*

Slide credit: E. Kalogerakis

# Limitations

- Many features are sensitive to topology



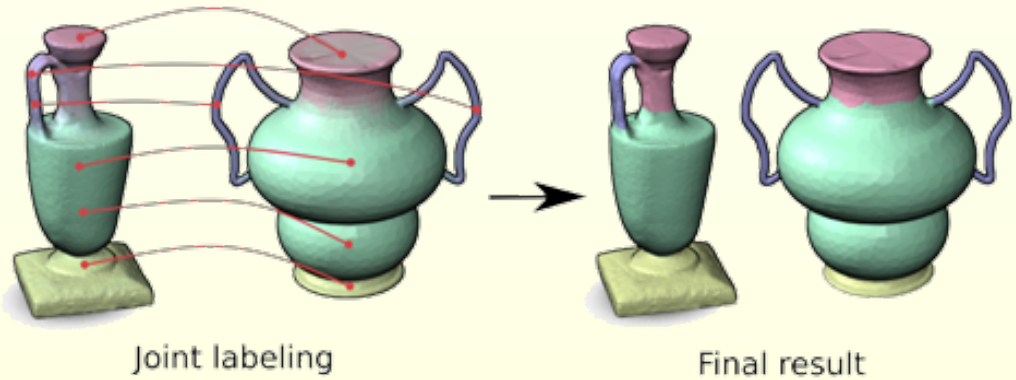

Slide credit: E. Kalogerakis

# More on learning shape labeling

- A follow-up: **“Prior Knowledge for Part Correspondence”** [van Kaick et al. 2011]

# More on learning shape labeling

- A follow-up: **"Prior Knowledge for Part Correspondence"** [van Kaick et al. 2011]
  - Similar problem formulation, combined with per-face mesh alignment



# Questions so far?

Unsupervised segmentation

# UNSUPERVISED CO-SEGMENTATION OF SHAPE COLLECTIONS

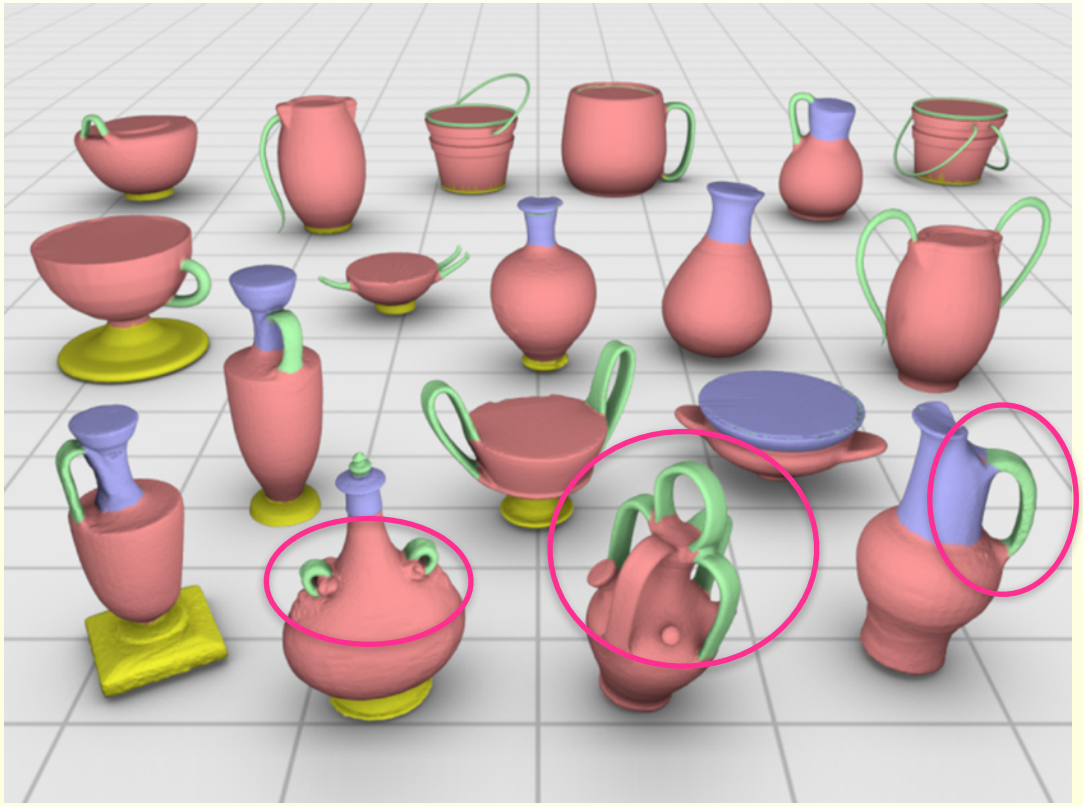
# Unsupervised co-segmentation in shape collections

- A collection of shapes sharing a general structure and functionality, but not necessarily similar corresponding parts

Slide credit: O. Sidi

# Unsupervised co-segmentation in shape collections

- Our goal: derive consistent segmentation across the collection
- Note the geometric and topological differences of parts!



E.g. handles

Slide credit: O. Sidi

# Unsupervised co-segmentation in shape collections

- **"Unsupervised Co-Segmentation of a Set of Shapes via Descriptor-Space Spectral Clustering"** [Sidi et al. 2011]

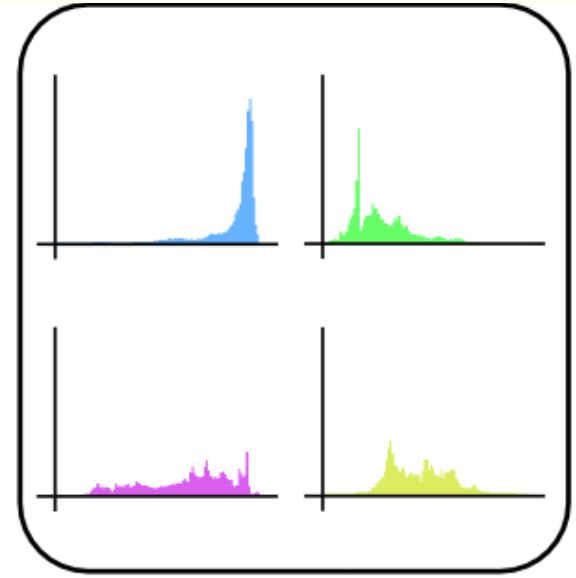
Main ideas

- Treat the segmentation problem as clustering in the space of shape descriptors rather than spatial coordinates
  - Pro: doesn't require spatially aligned shapes
- Spectral clustering using diffusion maps
- Create statistical models of shape part descriptors using obtained clusters
- Refine individual segmentations using graph cuts

# Unsupervised co-segmentation in shape collections

- Algorithm outline

1. Pre-segmentation

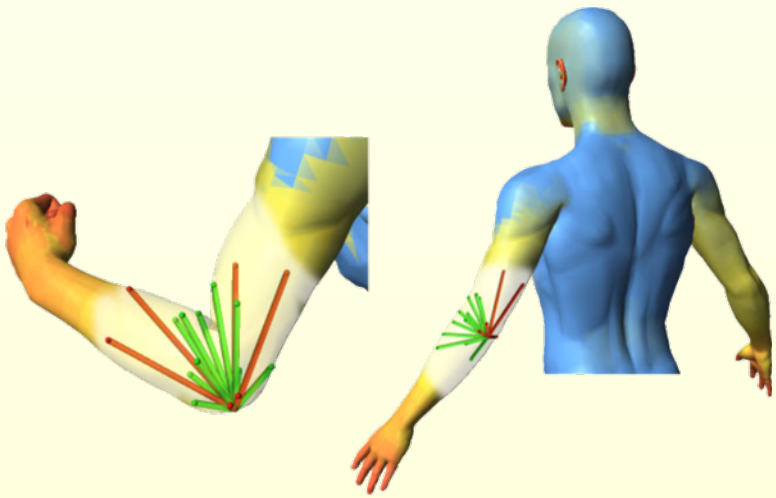


2. Statistical model
3. Segment descriptor
4. Segment embedding

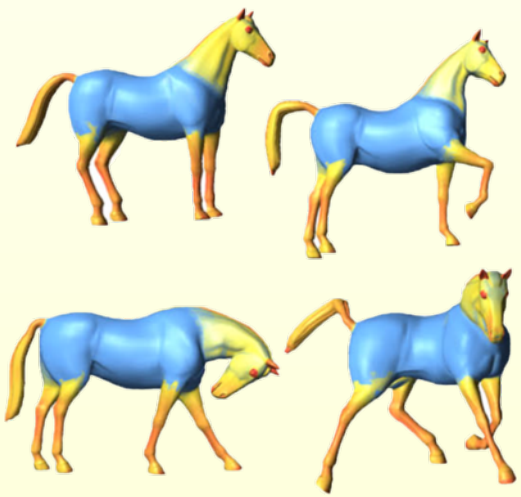
5. Clustering
6. Resulting

# Step 0: compute shape descriptors

- Input: scale-normalized shapes in upright orientation
- **Face-level descriptors**
  - Geodesic distance from the base of the shape
  - Angle between face normal and upright direction
  - <u>Shape diameter function</u> (SDF) [Shapira et al. 2009]



Examples of the cone of rays shot to the opposite side of the shape



SDF - weighted average of all ray lengths (see the paper for details)

Image credit: L. Shapira

# Step 1: pre-segmentation

- Initial (imperfect) segments obtained by *mean-shift clustering* [Comaniciu and Meyer 2002] applied to face descriptors

- **Segment-level descriptors**
  - Histograms of face-level descriptors per segment $h_i^d$ - for descriptor *d* and patch *i*
  - Segment area normalized by total shape area $a_i$
  - Segment geometry descriptor, derived from eigenvalues of PCA applied to segment vertices $g_i$

Image credit: O. Sidi

# Step 2: diffusion descriptor embedding

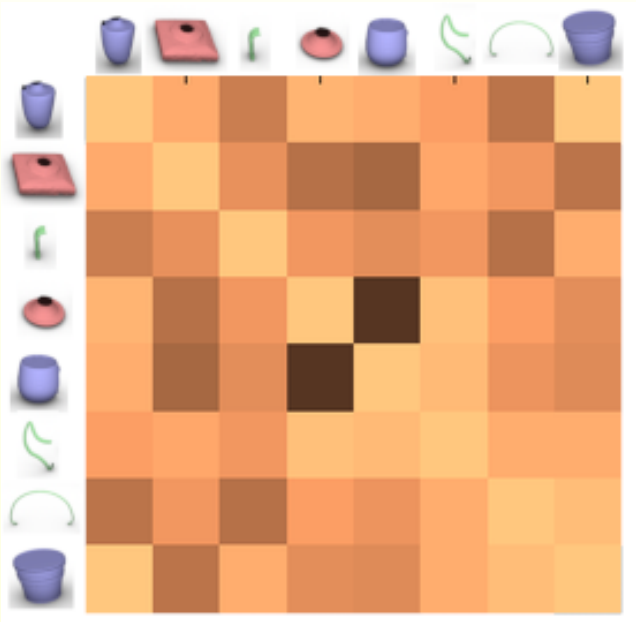
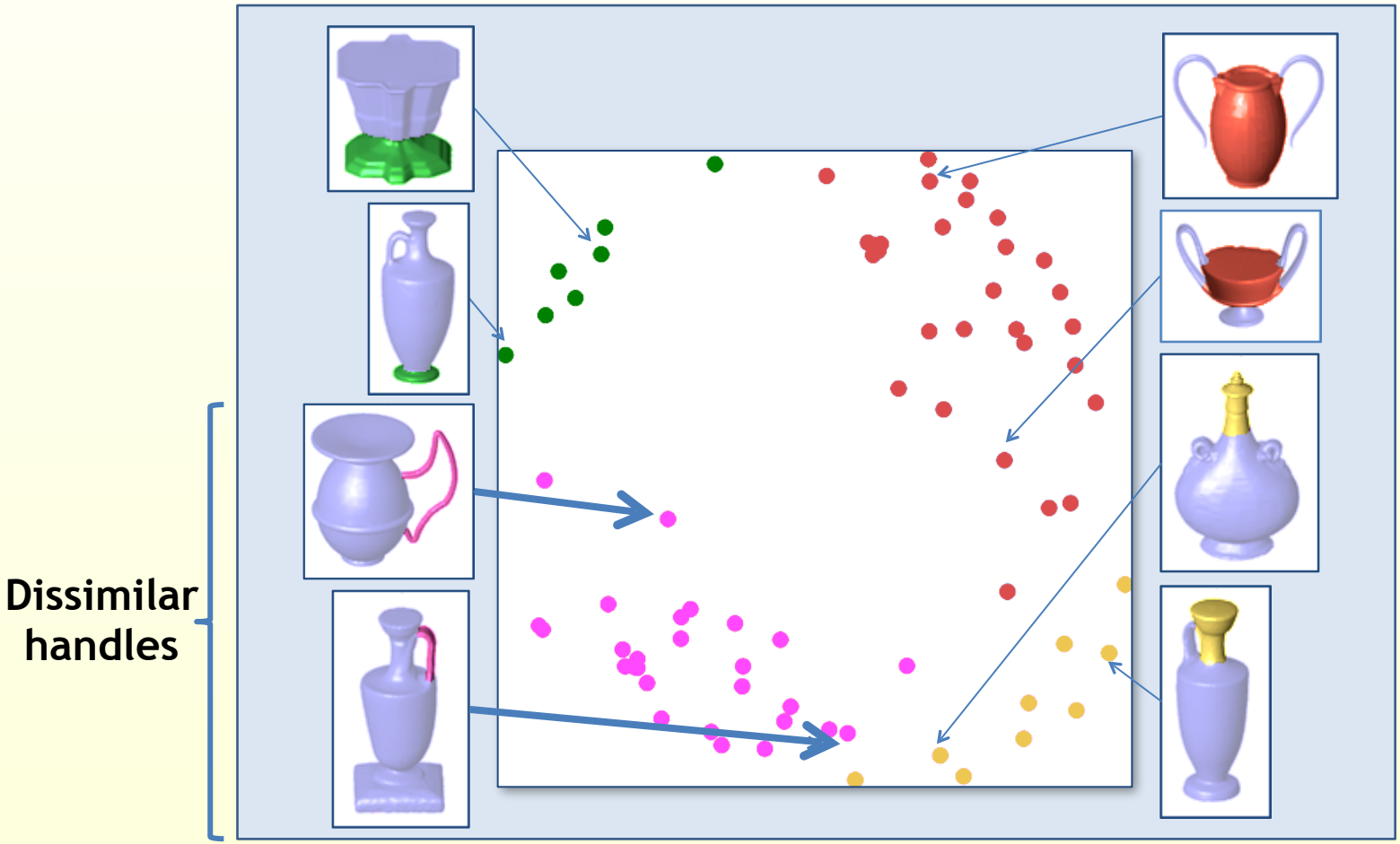


Image credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Applied to segment descriptors




Slide credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Applied to segment descriptors

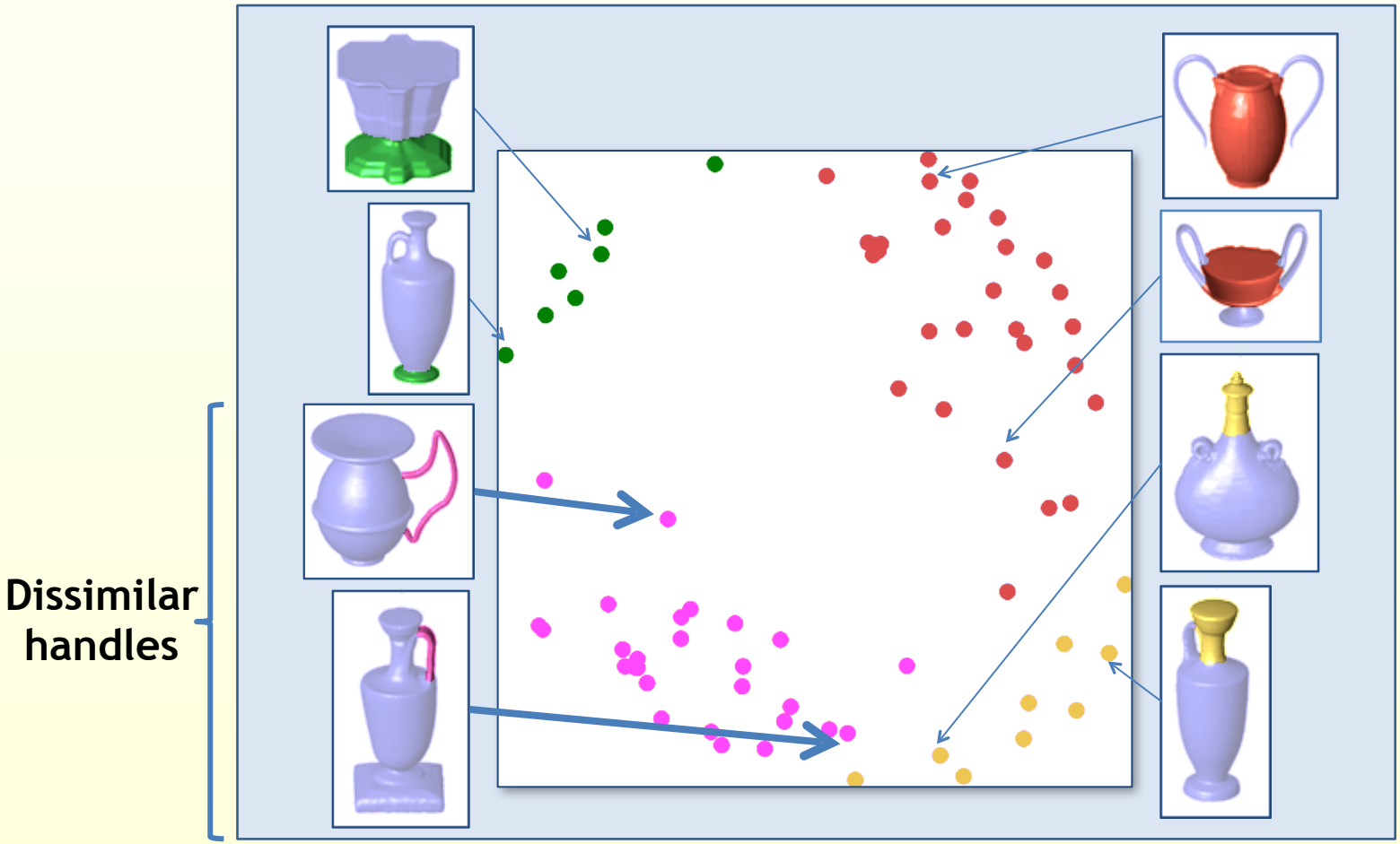



Image credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Applied to segment descriptors

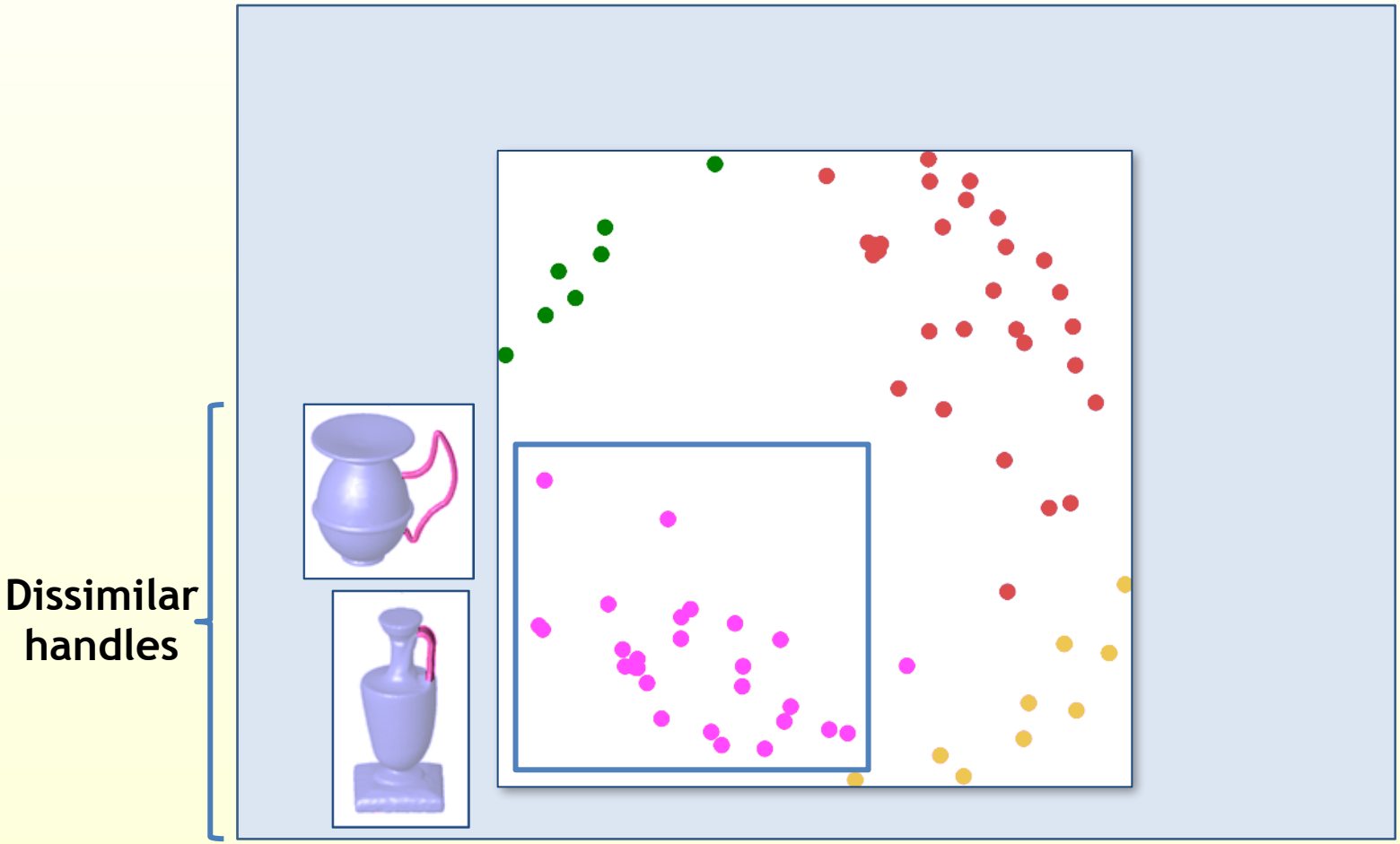



Image credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Third party connections

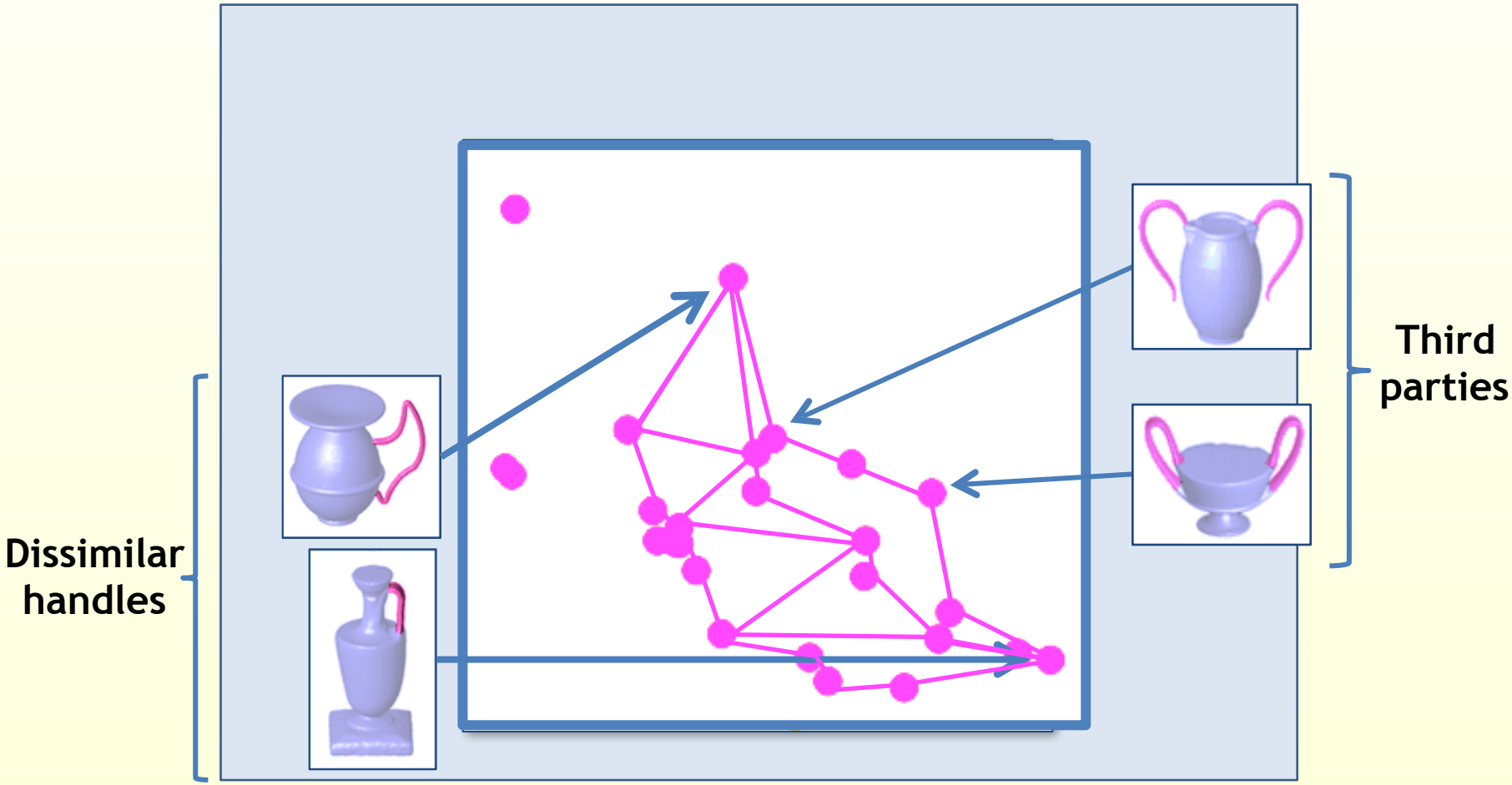



Image credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Diffusion map embedding via third parties

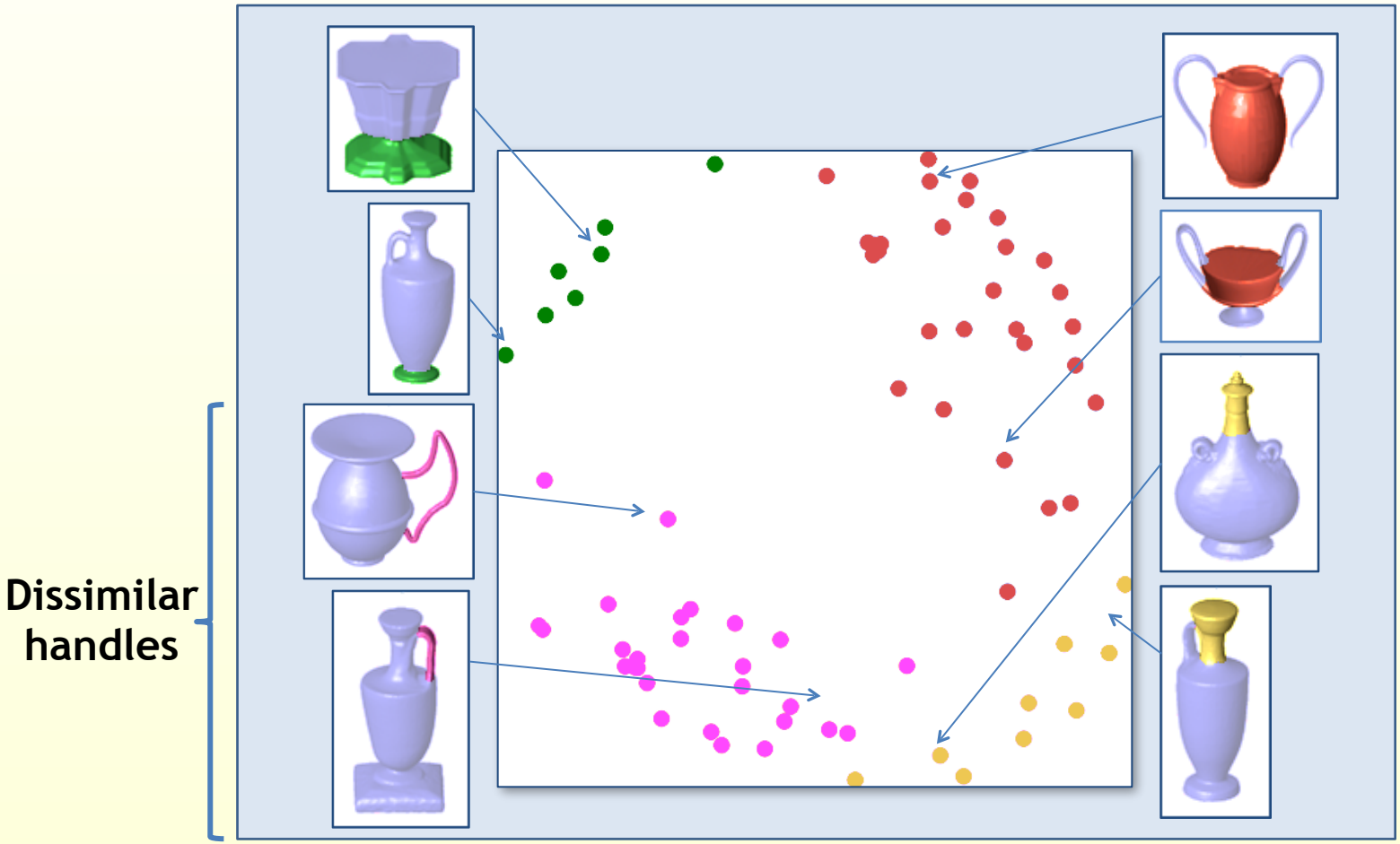



Image credit: O. Sidi

# Step 2: descriptor embedding - motivation

- Diffusion map embedding via third parties

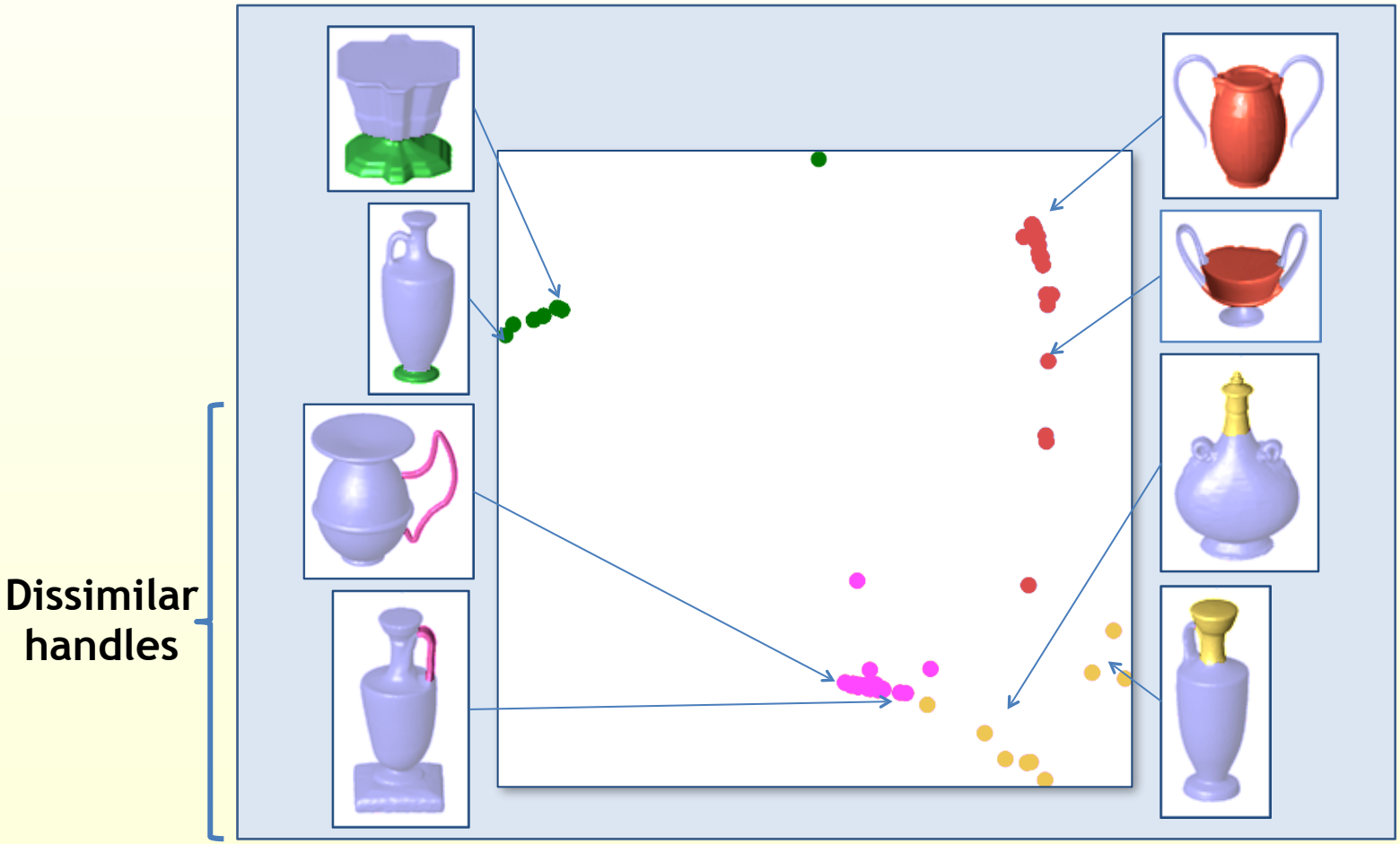
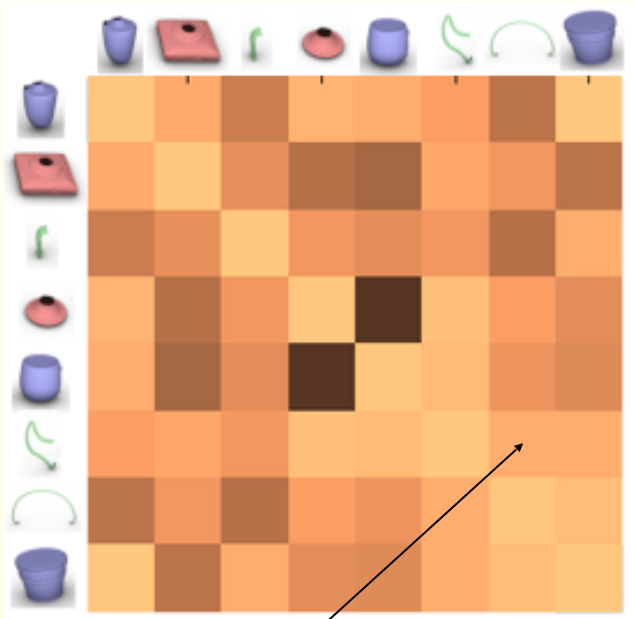


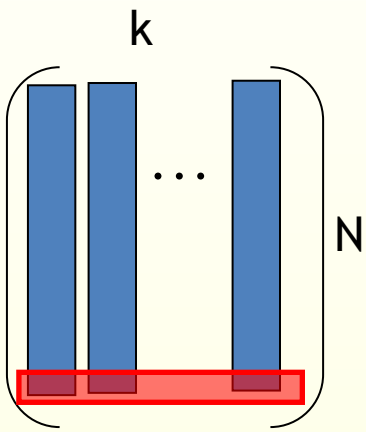

Image credit: O. Sidi

# Step 2: diffusion descriptor embedding



e.g. $A_{ij} = e^{-\frac{D(s_i,s_j)^2}{2\sigma^2}}$

* more details in the paper




k Leading eigenvectors normalized

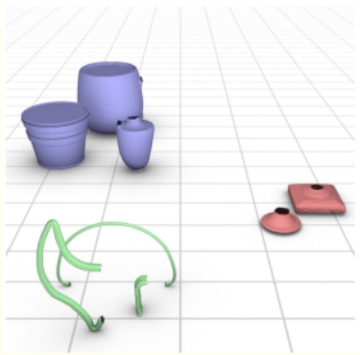
3 eigenvectors were used in the paper

$$\mathcal{D}(s_i, s_j) = \sqrt{\sum_{d=1}^{n_d} \mathrm{EMD}^2(h_i^d, h_j^d) + |a_i - a_j|^2 + \|g_i - g_j\|_2^2},$$

Image credit: O. Sidi

# Step 3: clustering in the embedding space

- Agglomerative hierarchical clustering [?] in the embedding space
- Number of classes given by the user



- Clustering gives an <u>initial co-segmentation</u>

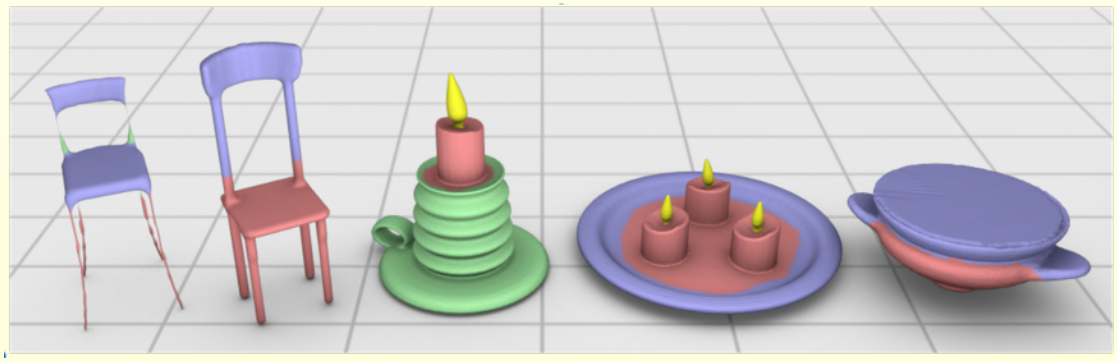
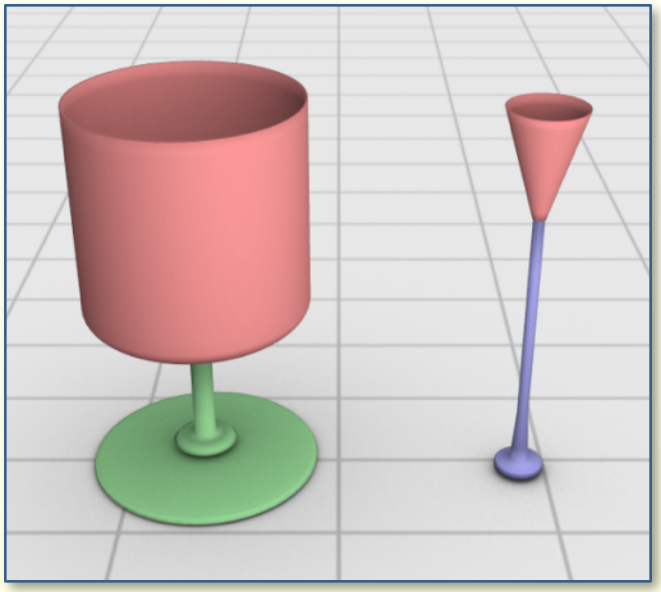
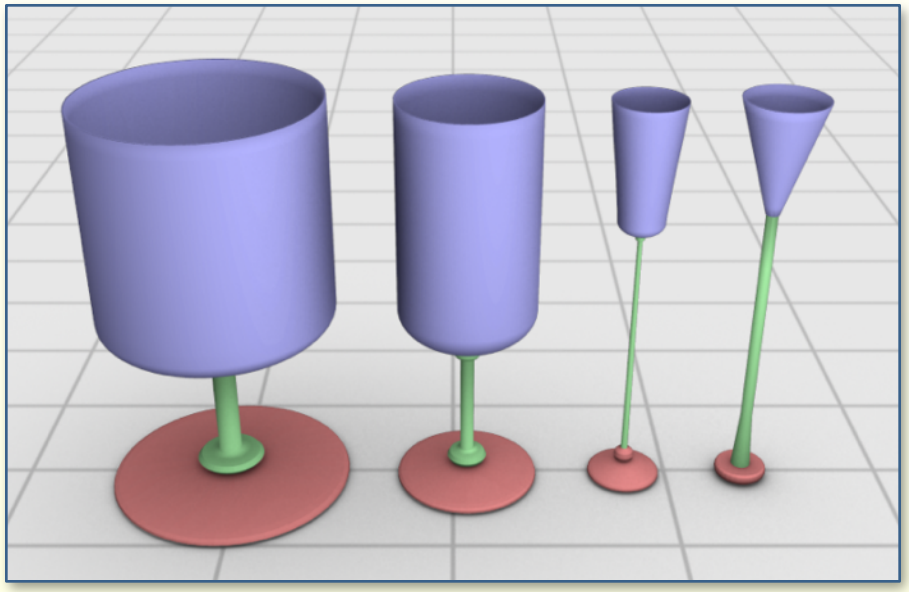


Image credit: O. Sidi

# Step 3: more results



Initial shapes

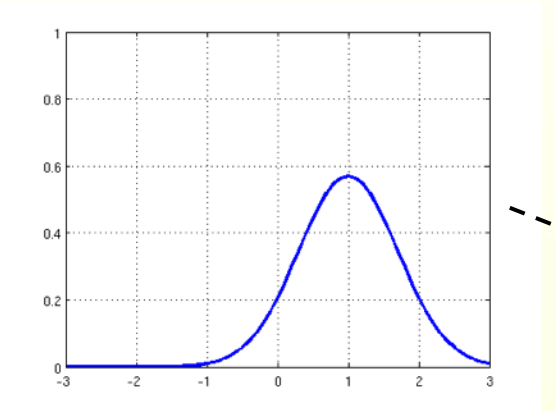


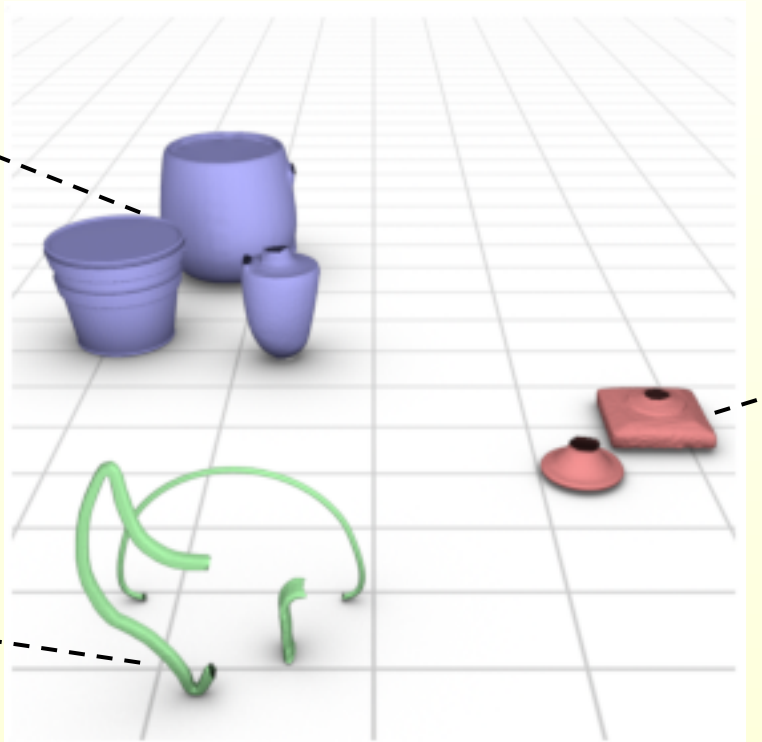
Descriptor space clustering

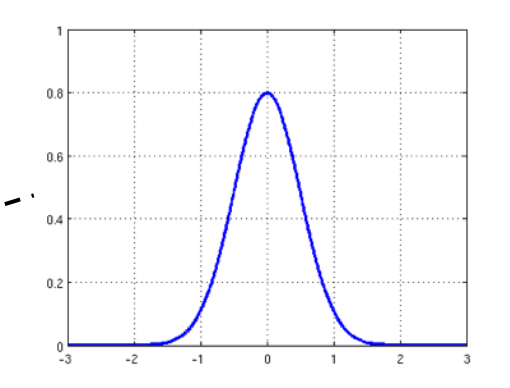
Image credit: O. Sidi

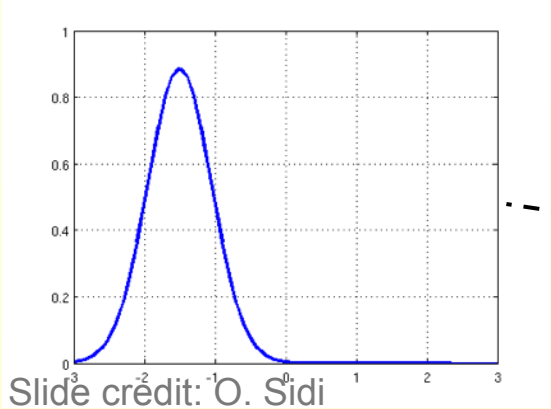
# Step 4: statistical model and labeling

- Goal: create statistical models of part descriptors to refine the segmentation





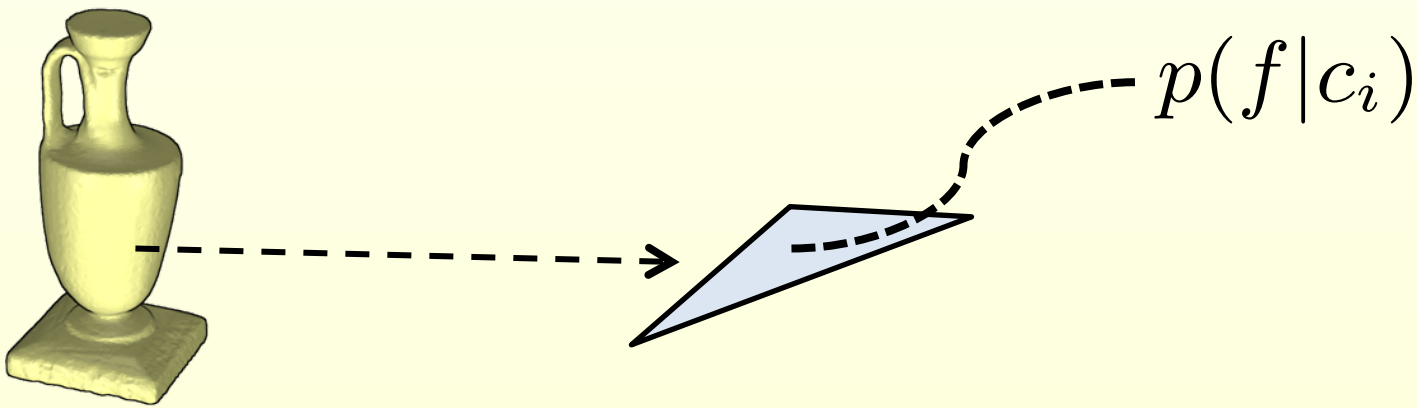

Slide credit: O. Sidi

# Step 4: statistical model and labeling

- Fit three-dimensional Gaussians to descriptors, using Expectation Maximization (EM)

$$p(f|c_i) = p(f, \mu_i, \Sigma_i) = C\, e^{-\frac{1}{2}(f-\mu_i)^T \Sigma_i^{-1}(f-\mu_i)}$$

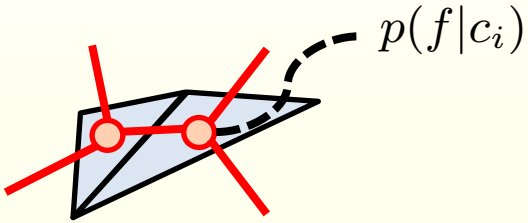
- Inference: probability of face belonging to class




Slide credit: O. Sidi

# Step 4: refined co-segmentation

- Graph cuts labeling based on learned statistical model
- Graph *(G,E)* given by triangle connectivity
  - Nodes in *G* correspond to triangles
  - Edges in *E* correspond to adjacent faces




- Energy functional

$$\mathcal{E}(l) = \sum_{u \in V} \mathcal{E}_D(u, l_u) \; + \sum_{uv \in E} \mathcal{E}_S(u, v, l_u, l_v)$$

- where $l_u$ and $l_v$ are the labels assigned to nodes *u* and *v* ; $\mathcal{E}_D$ and $\mathcal{E}_S$ are the data and smoothness energy terms

Image credit: O. Sidi

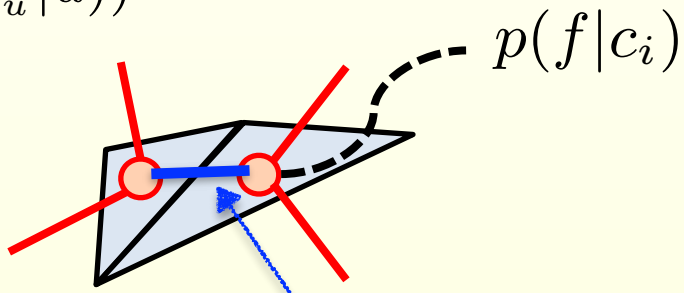
# Step 4: refined co-segmentation

$$\mathcal{E}(l) = \sum_{u \in V} \mathcal{E}_D(u, l_u) + \sum_{uv \in E} \mathcal{E}_S(u, v, l_u, l_v)$$

How well label *l* matches face *u*?

Is it a good place for a cut?

- Data term: $\mathcal{E}_D(u, l_u) = -\omega \log(p(c_{l_u}|u))$




edge length

- Smoothness term:

$$\mathcal{E}_S(u, v, l_u, l_v) = \begin{cases} 0, & \text{if } l_u = l_v \\ -\log(\theta_{uv}/\pi)\, l_{uv}, & \text{otherwise} \end{cases}$$

(similar to [Shapira et al. 2009])

dihedral angle between faces

Image credit: O. Sidi

# Step 4 result - final co-segmentation

Clustering result

Graph cut result

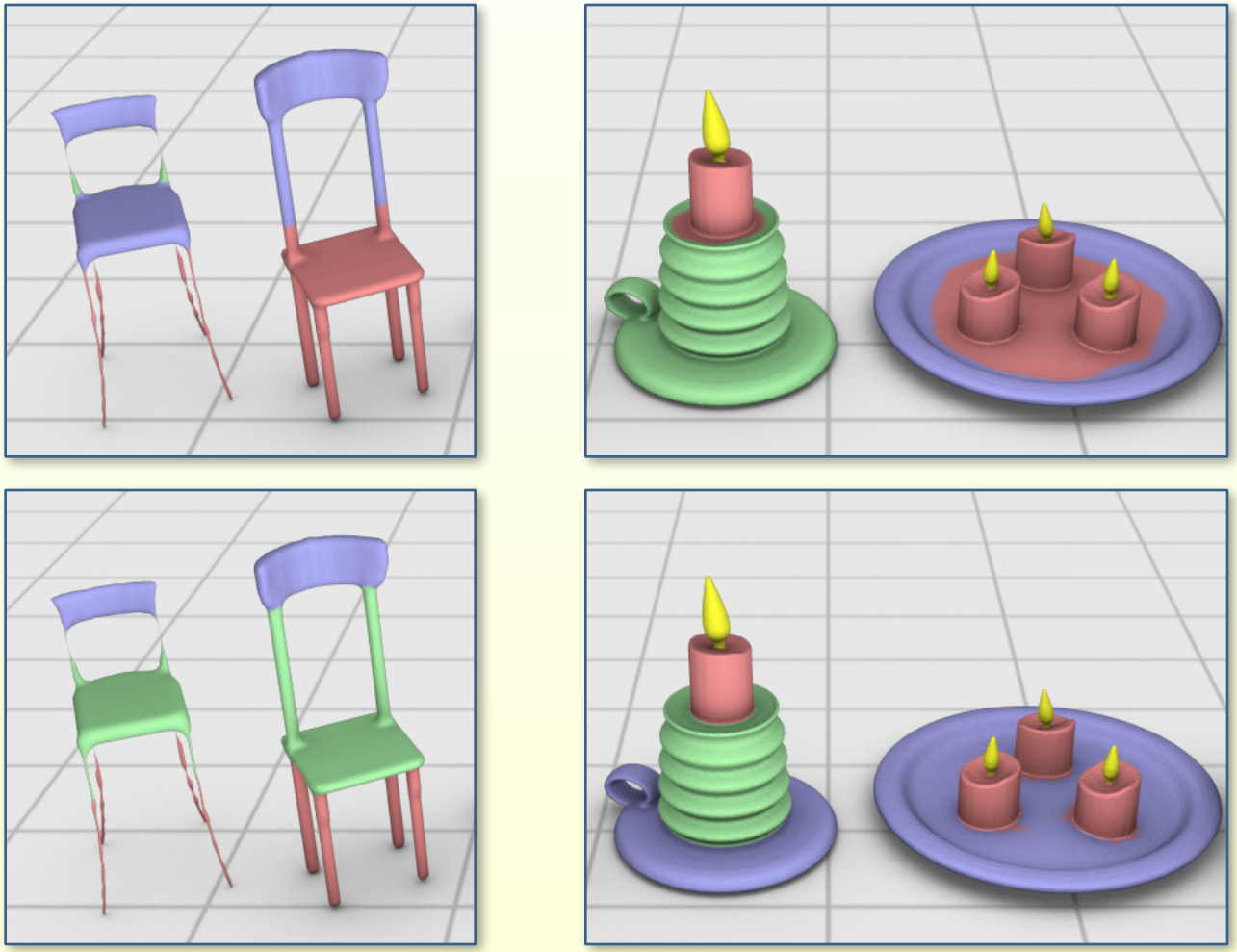


Image credit: O. Sidi

# Results

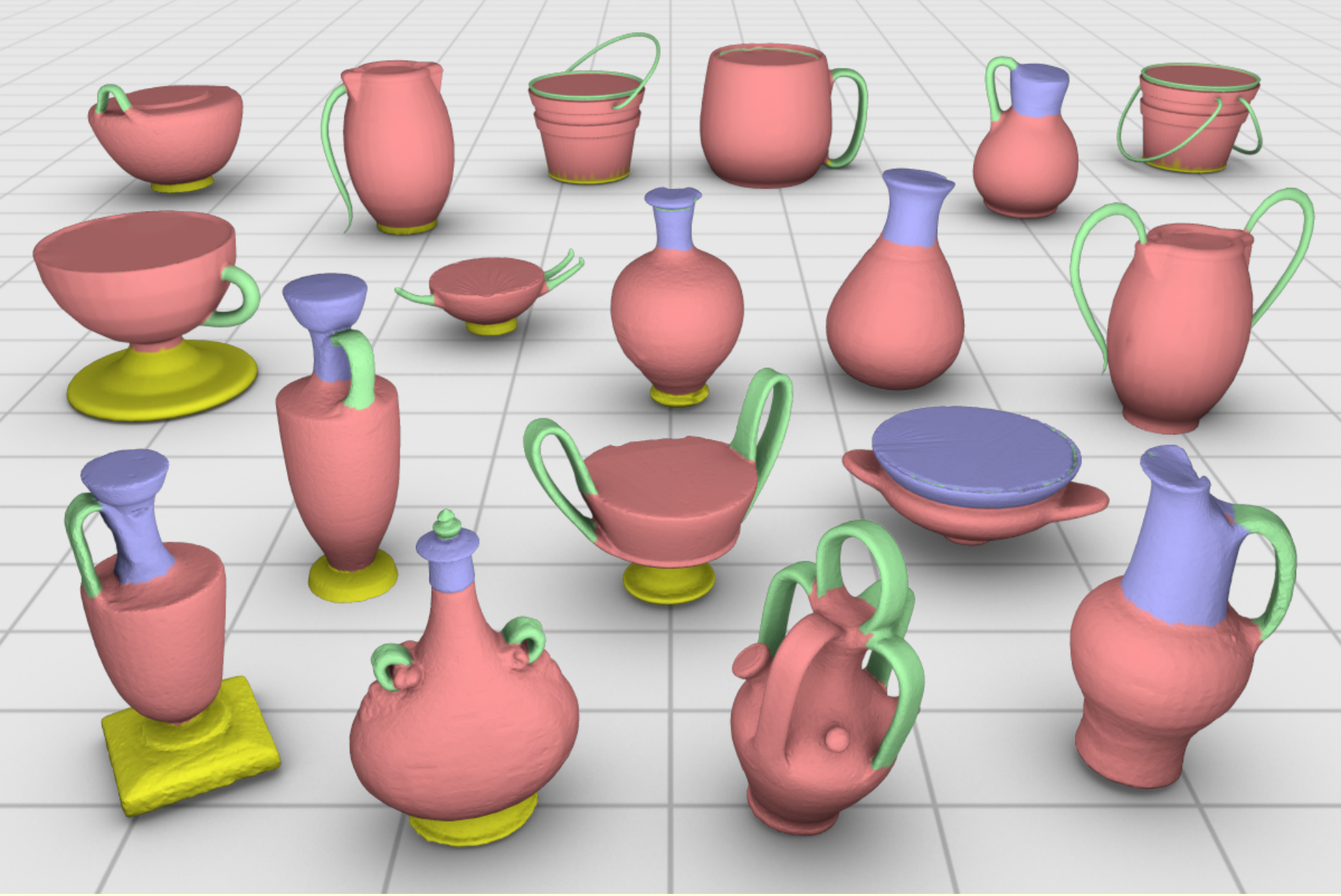
- Dataset: seven sets of shapes
  - Man-made shapes

    [van Kaick et al. 2011]
  - Organic shapes

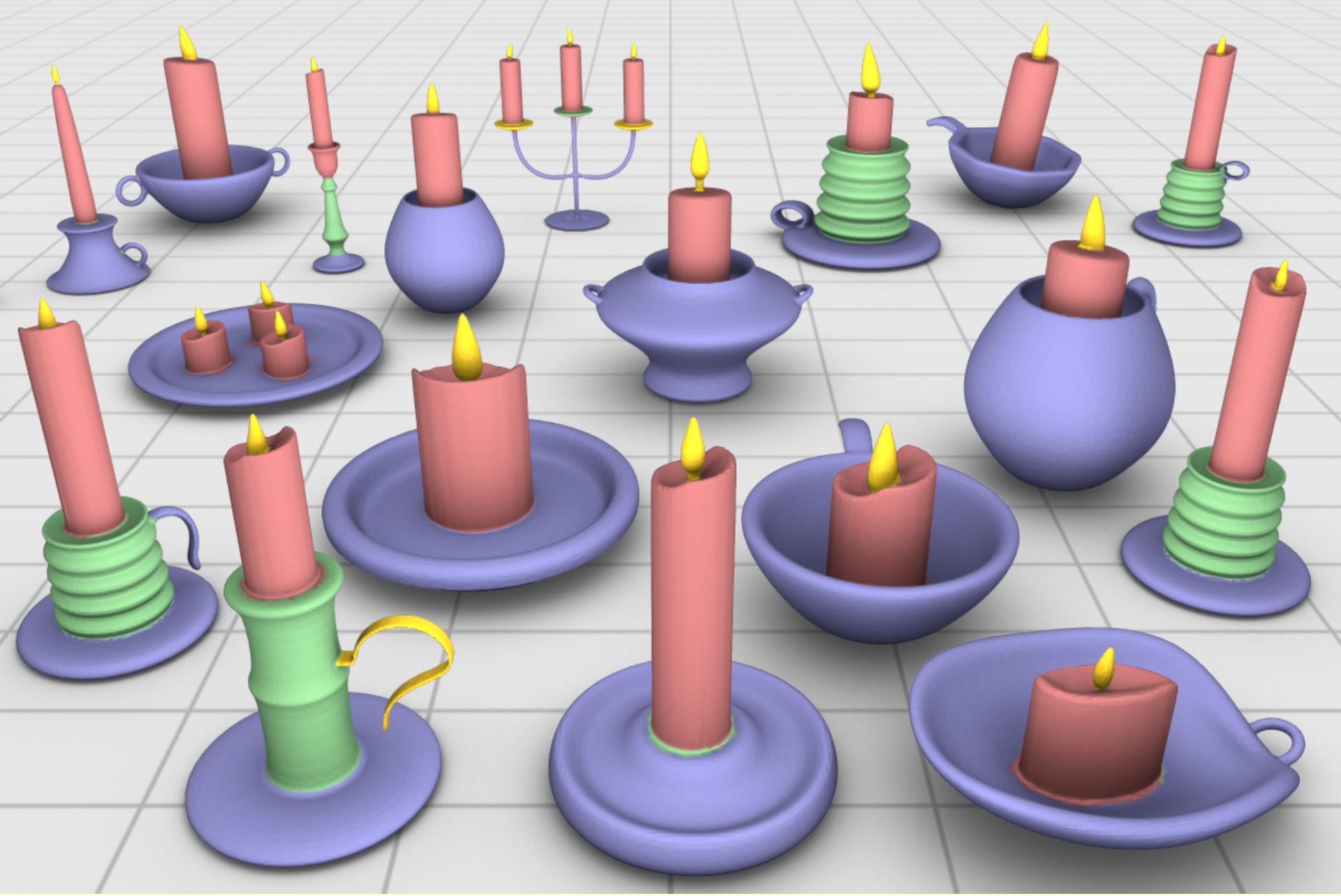
    [Kalogerakis et al. 2010, Chen et al. 2009]

- Variability in geometry and part composition

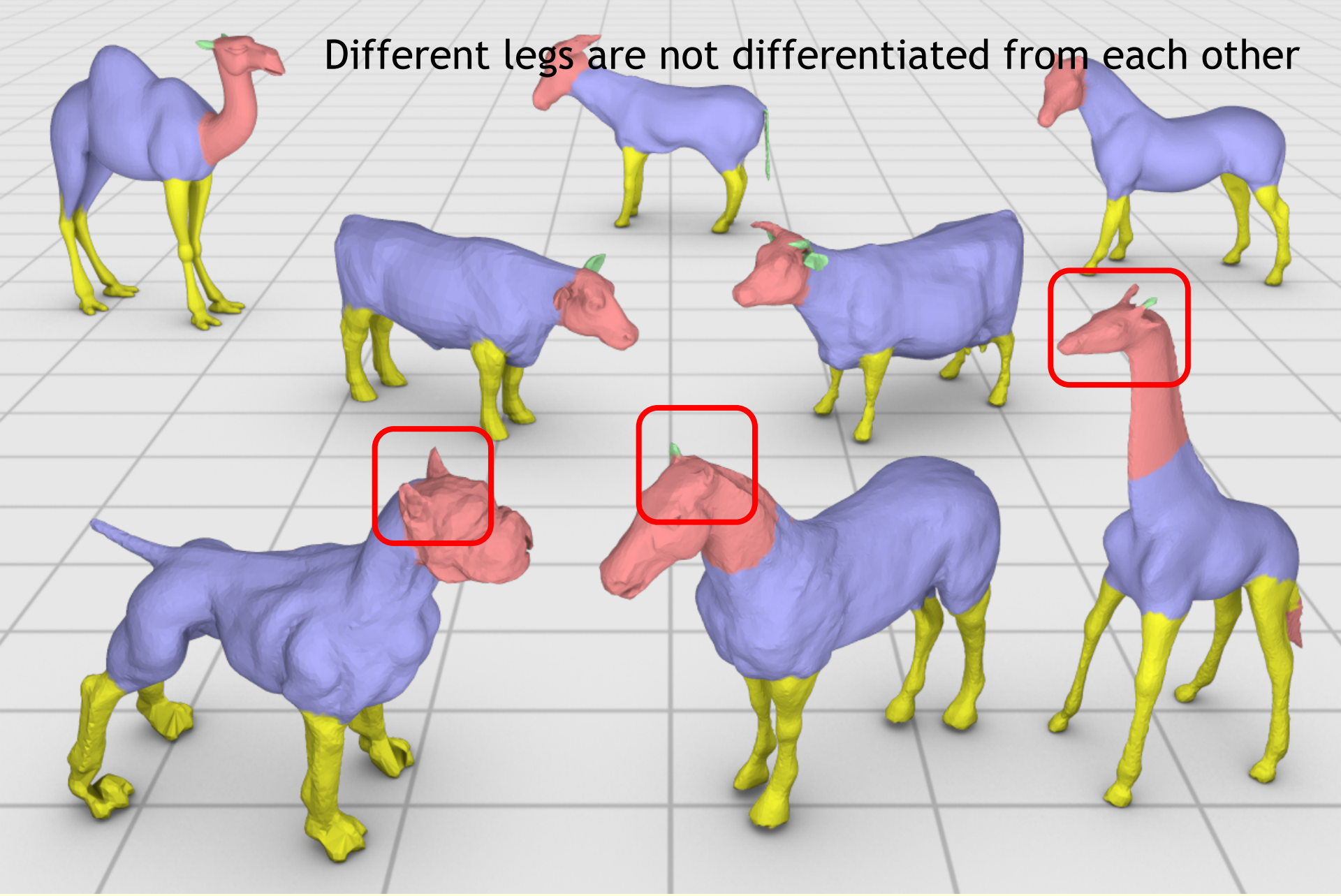
Slide credit: O. Sidi



Slide credit: O. Sidi



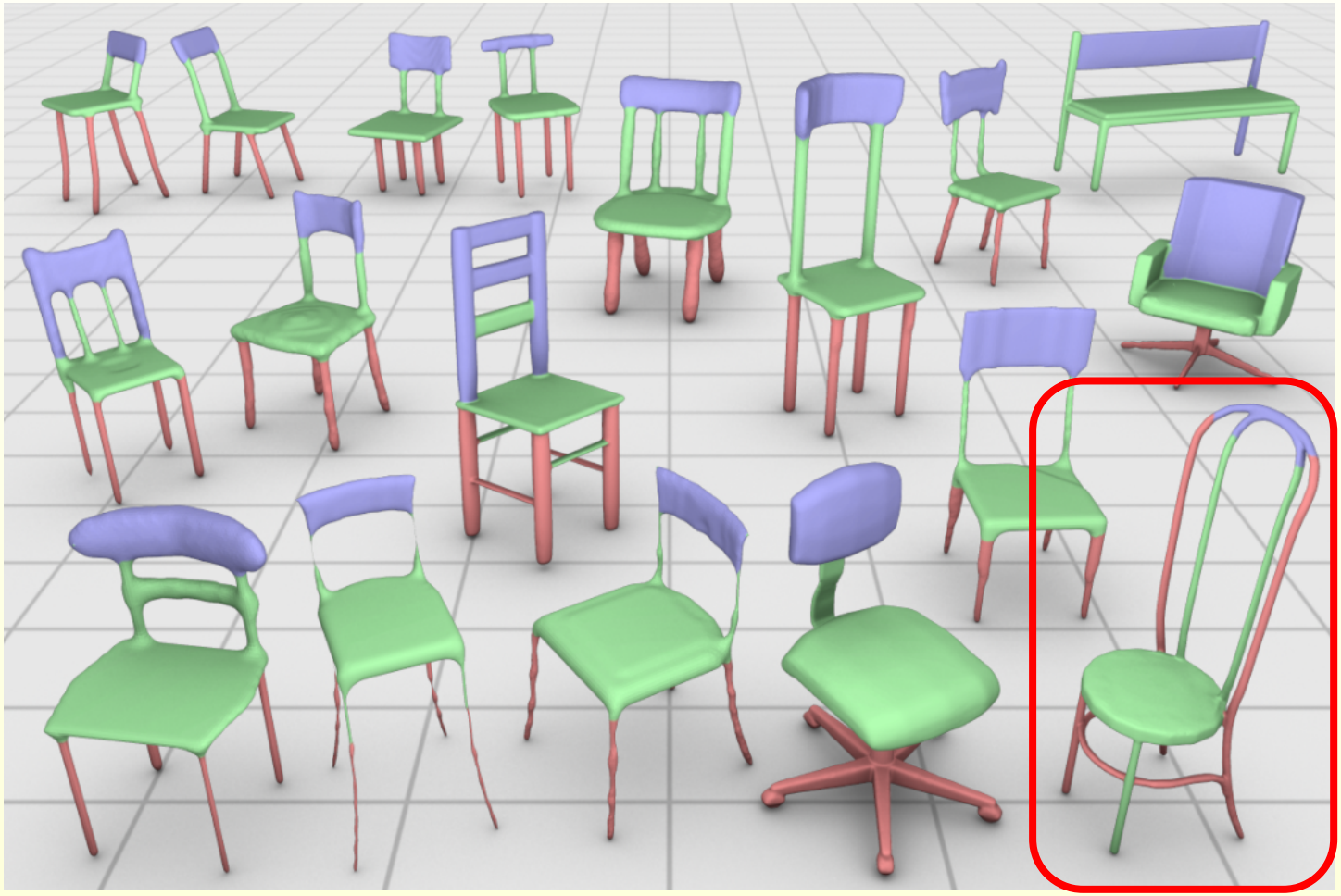
Slide credit: O. Sidi




Limitation: small components like ears and horns are not consistently segmented

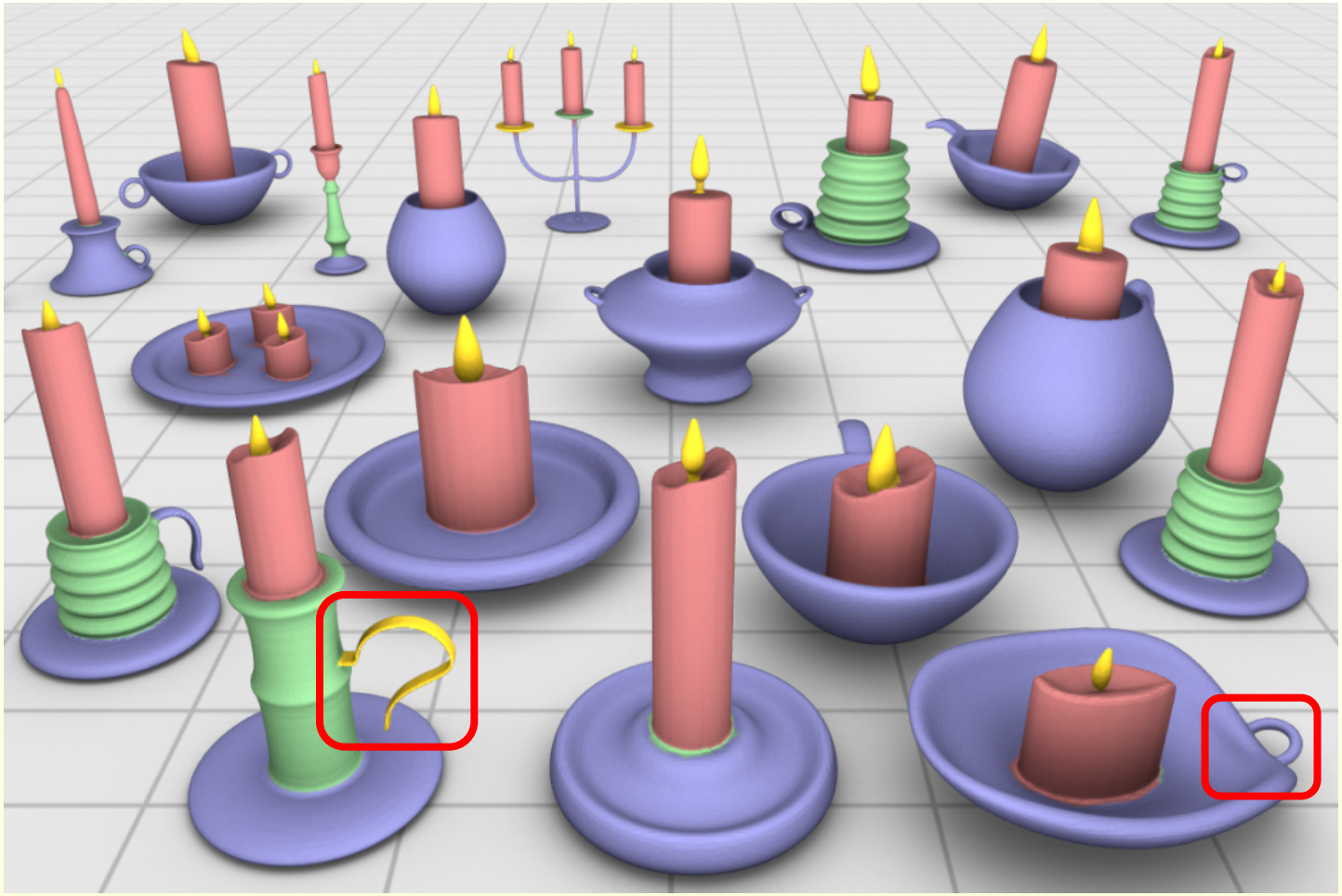
Slide credit: O. Sidi

# Limitations: lack of third parties



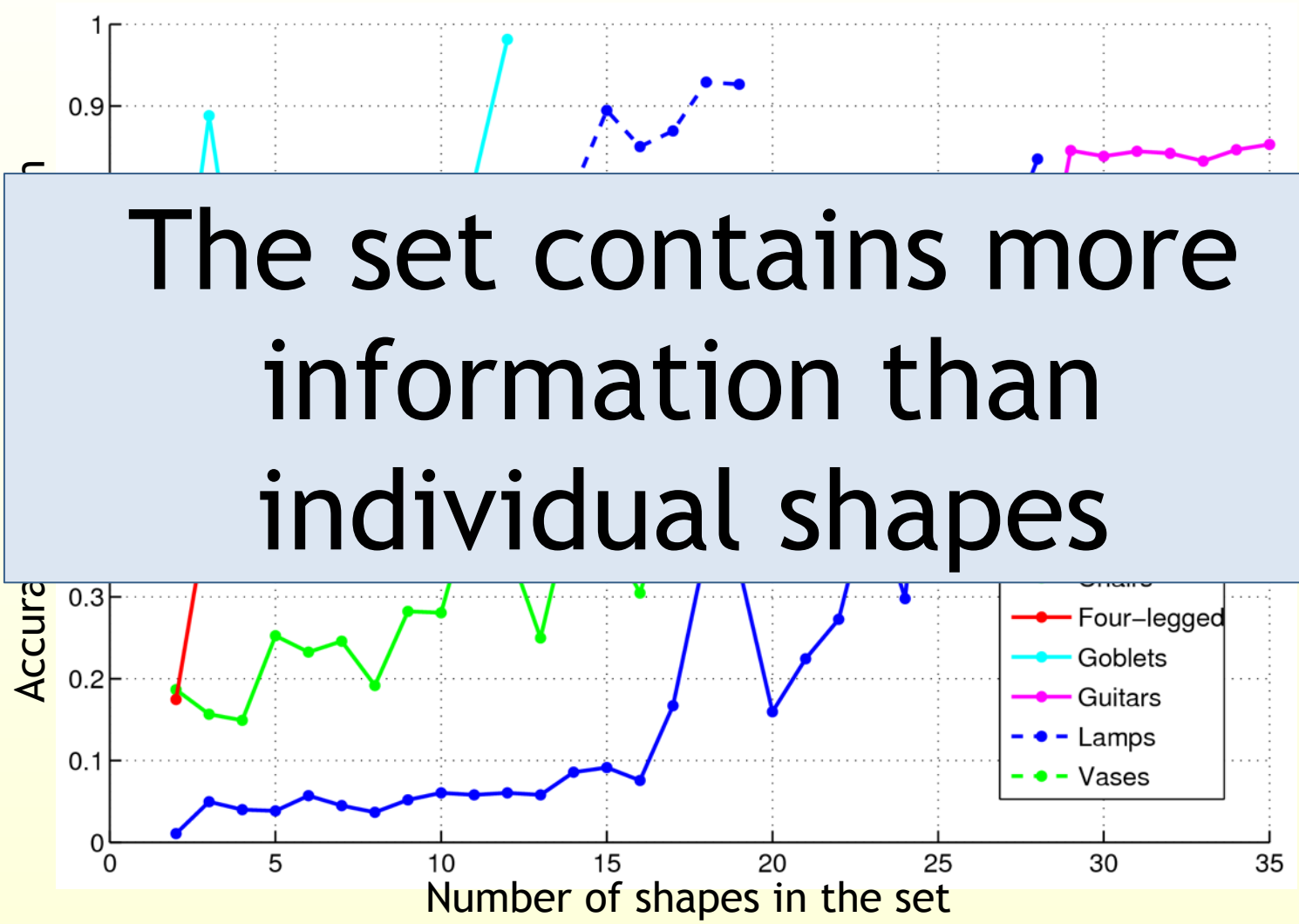
Slide credit: O. Sidi

# Limitations: incorrect connections



Slide credit: O. Sidi

# Effect of the set on the accuracy




The set contains more information than individual shapes

Slide credit: O. Sidi

# Descriptor clustering - different flavor

- A follow-up work: **"Co-Segmentation of 3D Shapes via Subspace Clustering"**, Hu et al. 2012

- Previous method [Sidi et al. 2011]
  - Relies on pre-segmentation
  - ▶ affects quality of final result

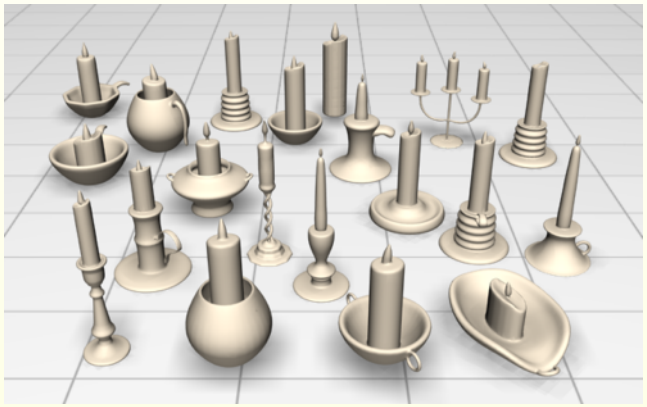
Pre-segmentation

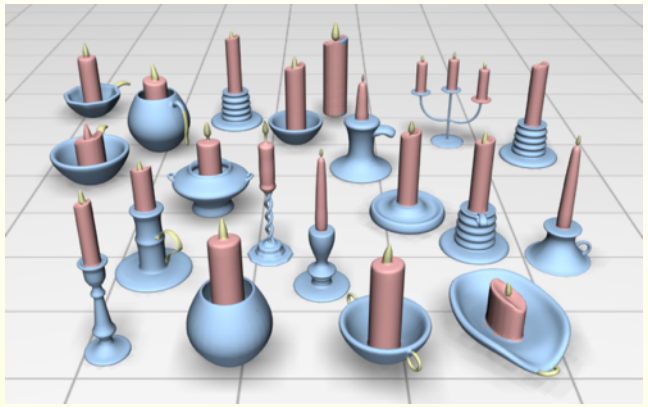
  - Uses SDF + simple descriptors
  - ▶ can we use more advanced descriptors?

Image credit: O. Sidi

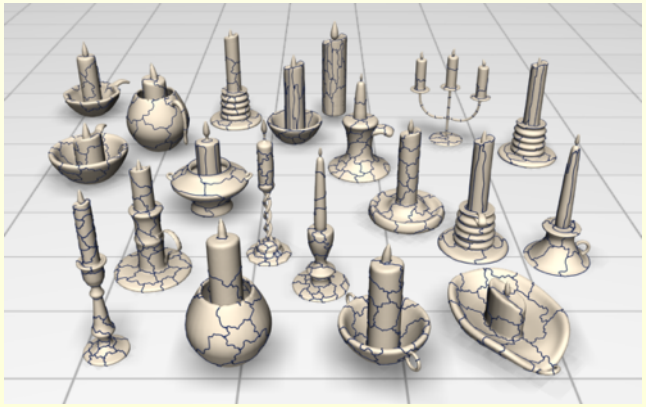
# Co-segmentation via subspace clustering

- Utilize over-segmentation to create initial segments





**Over-segmentation**
[Huang et al. 2011]

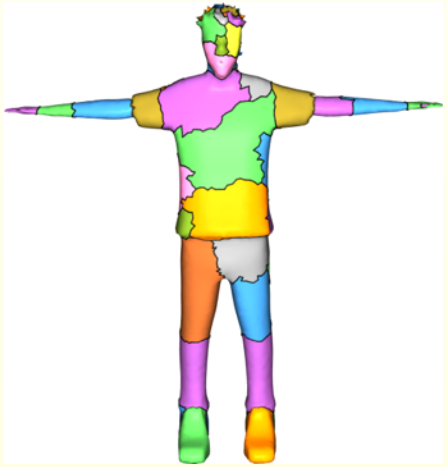


**Unsupervised**

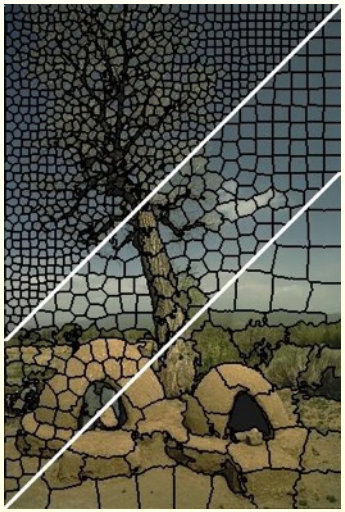
Slide credit: R. Hu

# Over-segmentation

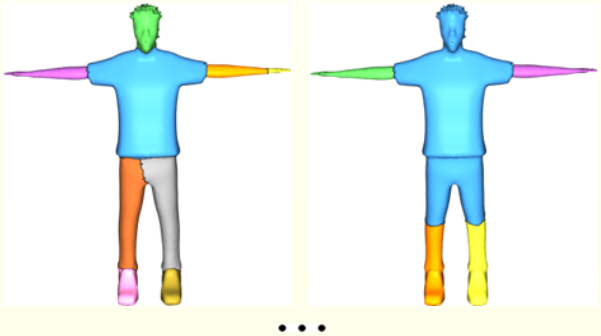
- Segmentation parameterization [Huang et al. 2011]



Patches
[Golovinskiy and Funkhouser 08]



Super-pixels
[Ren and Malik 03]



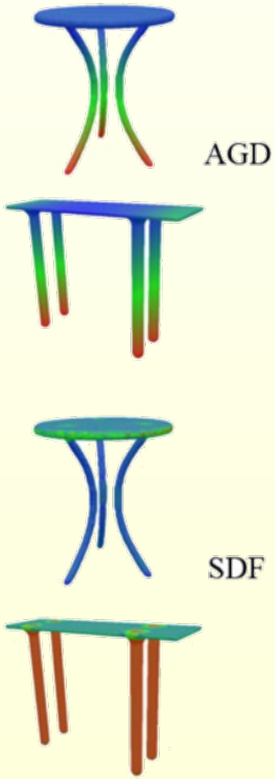
Randomized Cuts

Initial Segments

Slide credit: R. Hu

# Co-segmentation via subspace clustering: key observation

- “two parts of models perceived as corresponding may not necessarily be similar in all features and may even significantly differ on some”

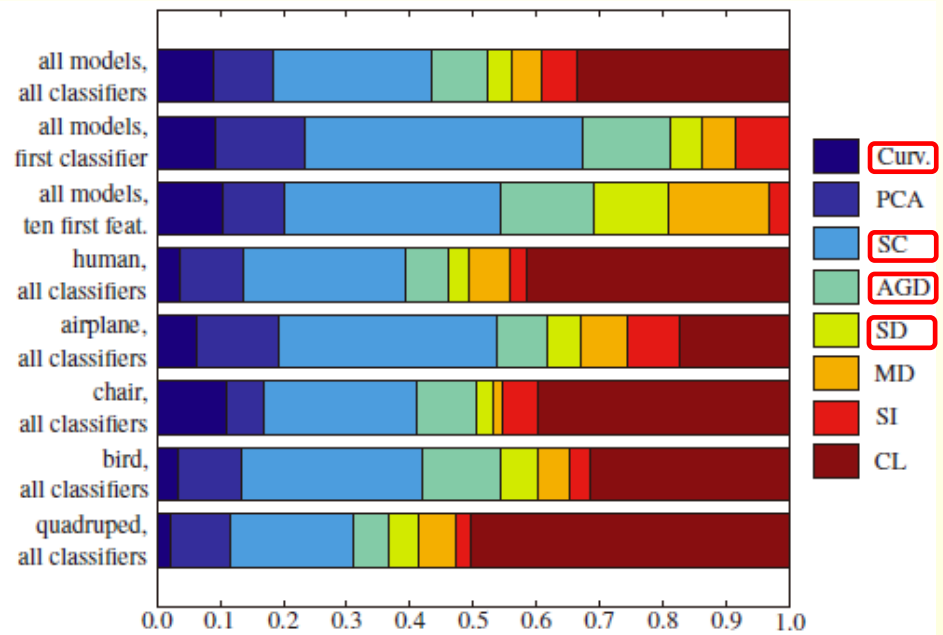



Chair legs are quite similar in AGD features (upper right) while they differ a lot in SDF features (lower right)

Slide credit: R. Hu

# Choice of features

- Different sets favor different features
  - Single feature is not enough



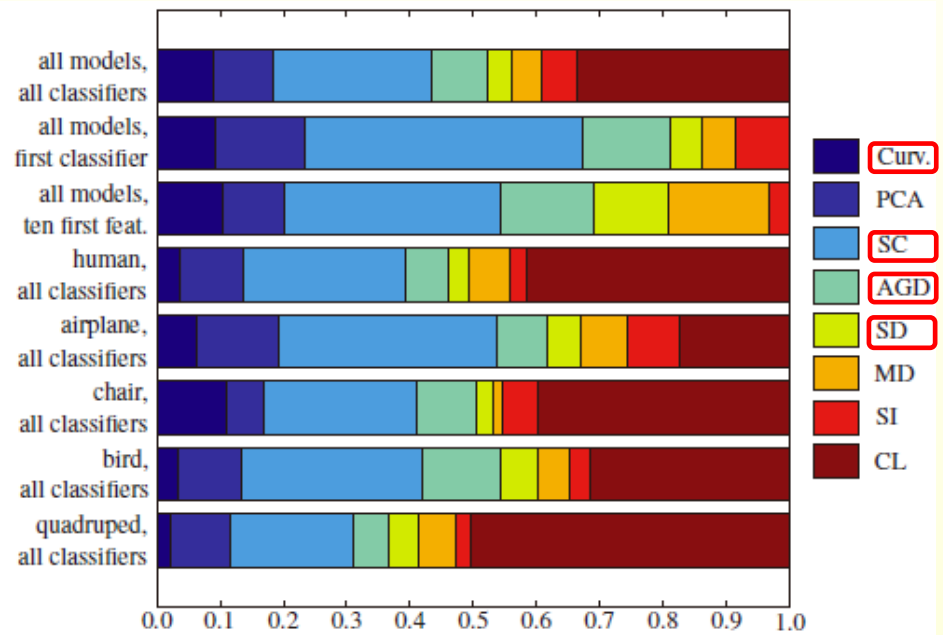

[Kalogerakis et al. 2010]

- Curvature
- Shape context
- Average geodesic distance
- Shape diameter (function)

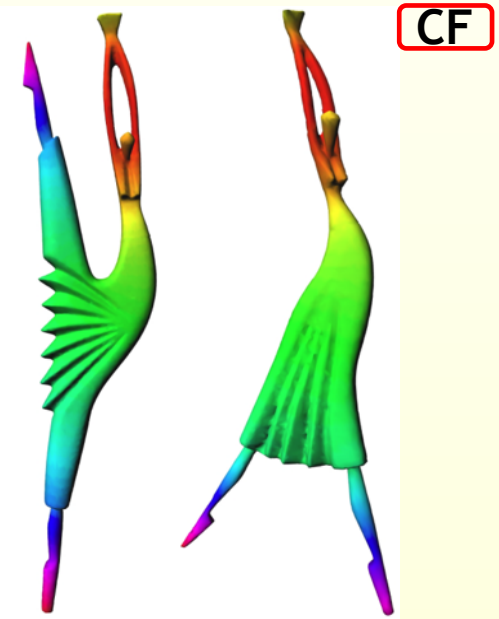
Slide credit: R. Hu

# Choice of features

- Different sets favor different features
  - Single feature is not enough




[Kalogerakis et al. 2010]

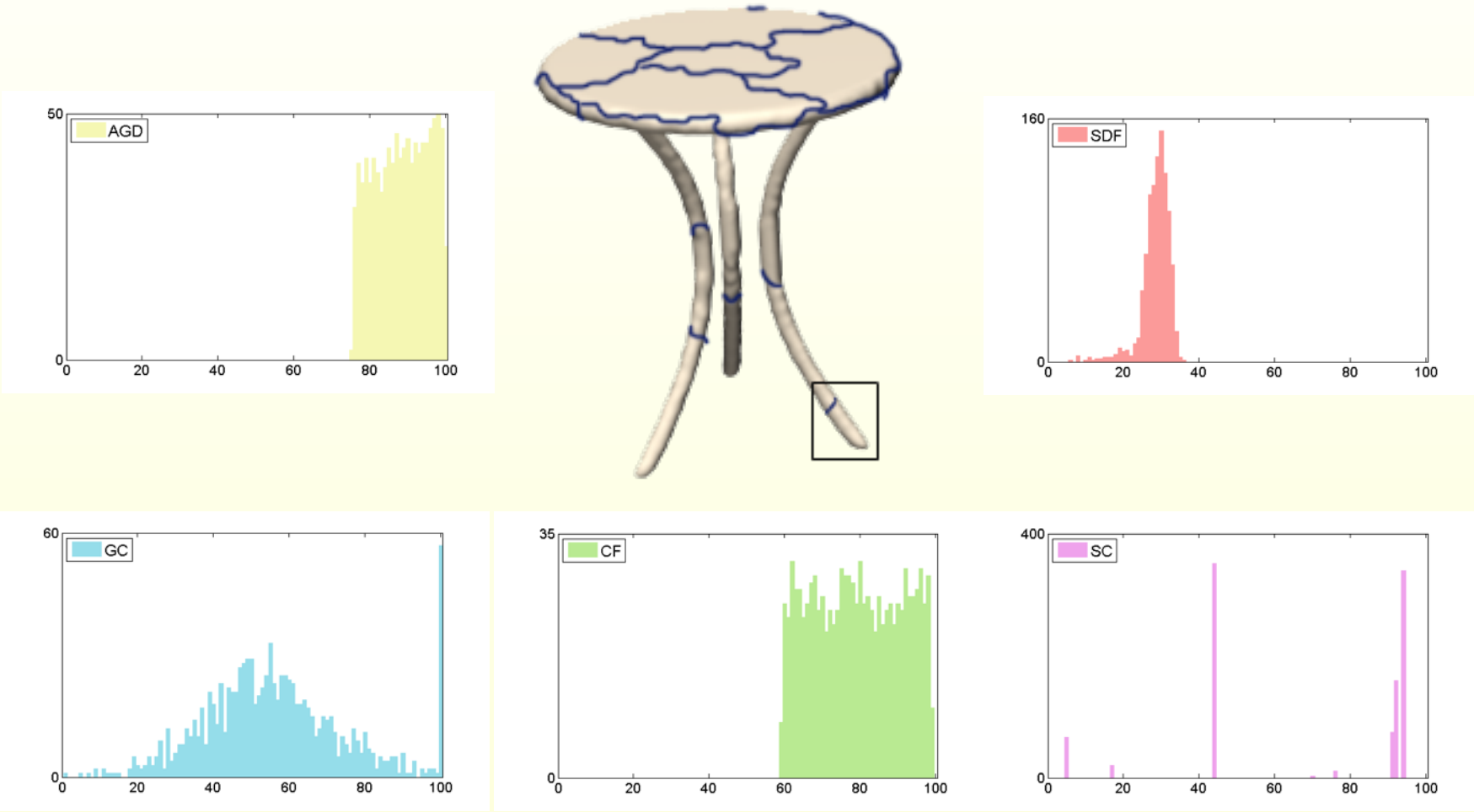



[Ben-Chen and Gostman 2008]

- Conformal factor

Slide credit: R. Hu

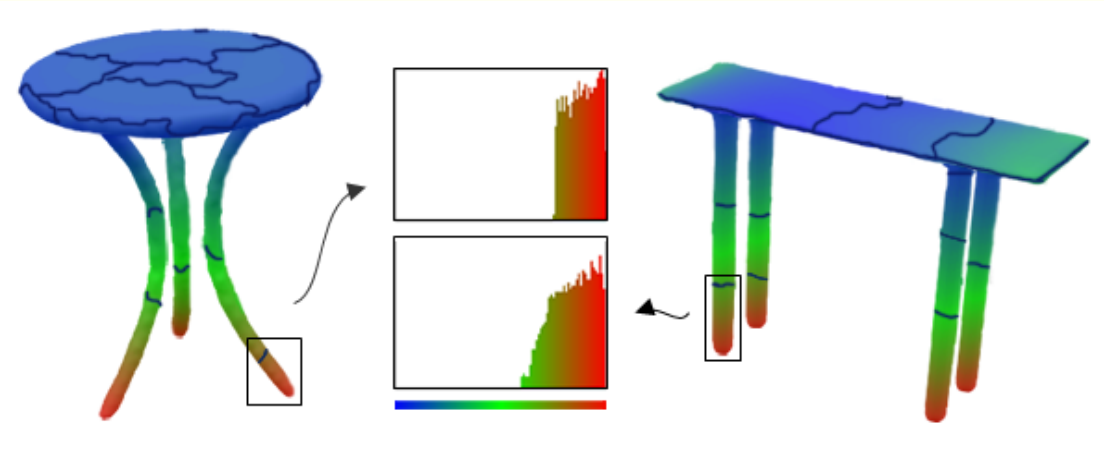
# Patch features given by histograms




Slide credit: R. Hu

# Co-segmentation via subspace clustering: key observation

- Idea 1: corresponding patches lie in <u>common subspaces</u> of some features (but not necessarily all features)



AGD

**Co-segmentation**

Key idea 1

**Subspace clustering**

Key idea 2

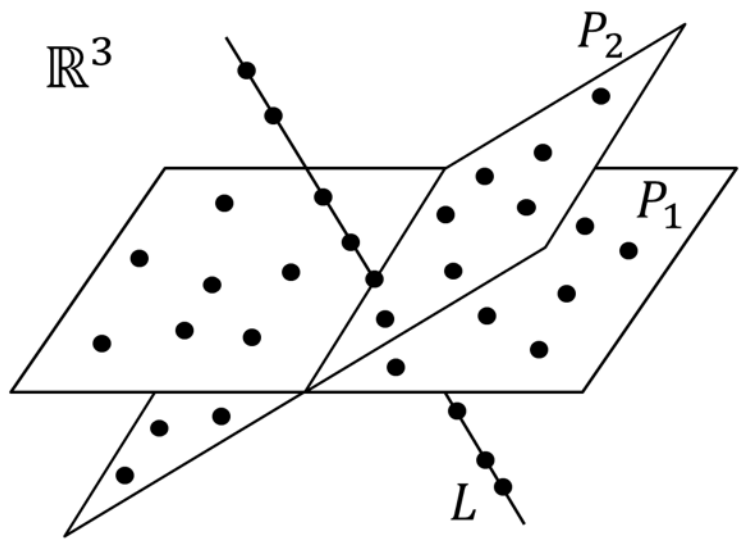
- Idea 2: “two patches are considered as similar if they are similar in a subset of feature spaces and have large similarity measurement in each of these feature spaces"

Slide credit: R. Hu

# Background: subspace clustering

[Vidal 2010]

- Input:
  - high dimensional datasets having low intrinsic dimensions
  - $\{x_j\}_{j=1,\ldots,N}, x_t \in \mathbb{R}^D$

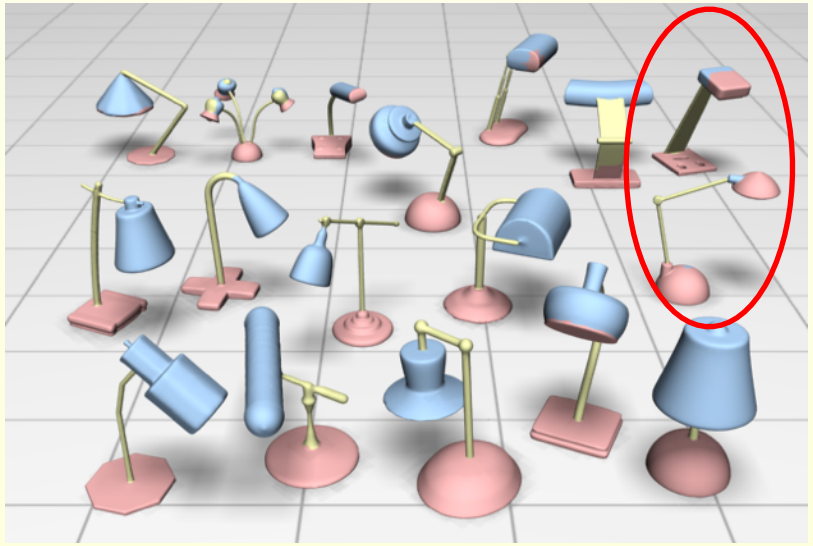



- Output:
  - multiple low-dimensional linear subspaces
  - $L, P_1, P_2$

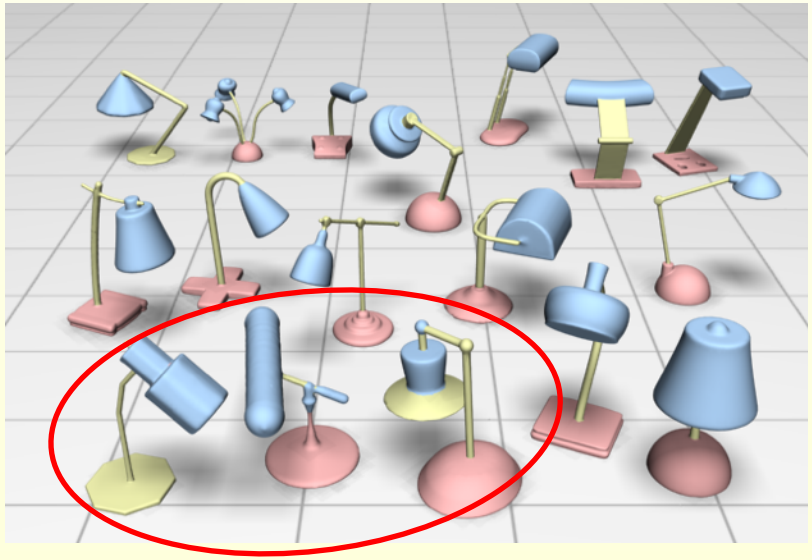
Slide credit: R. Hu

# Sub-space clustering: technical details

- Sub-space clustering performed via quadratic programming
- Smart penalty allows to finds a <u>subset of similar patch pairs</u>, and a <u>subset of features</u> to measure their similarity
- Refine part boundaries using <u>graph cuts</u>



Our algorithm



[Sidi et al. 2011]

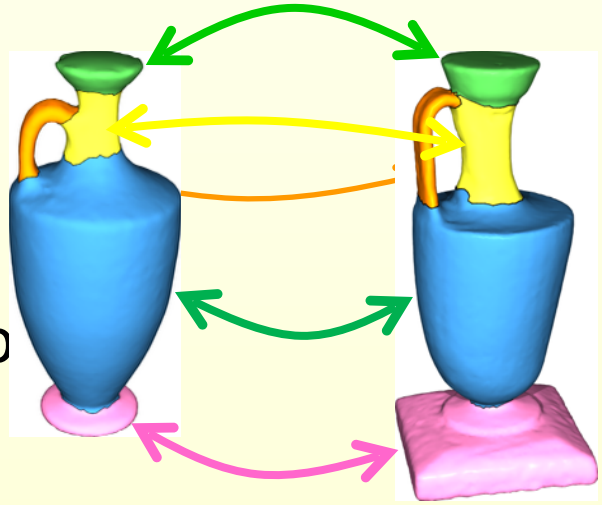
Slide credit: R. Hu

# Unsupervised co-segmentation as optimization problem

- **"Joint Shape Segmentation with Linear Programing"** [Huang et al. 2011]
- Objective

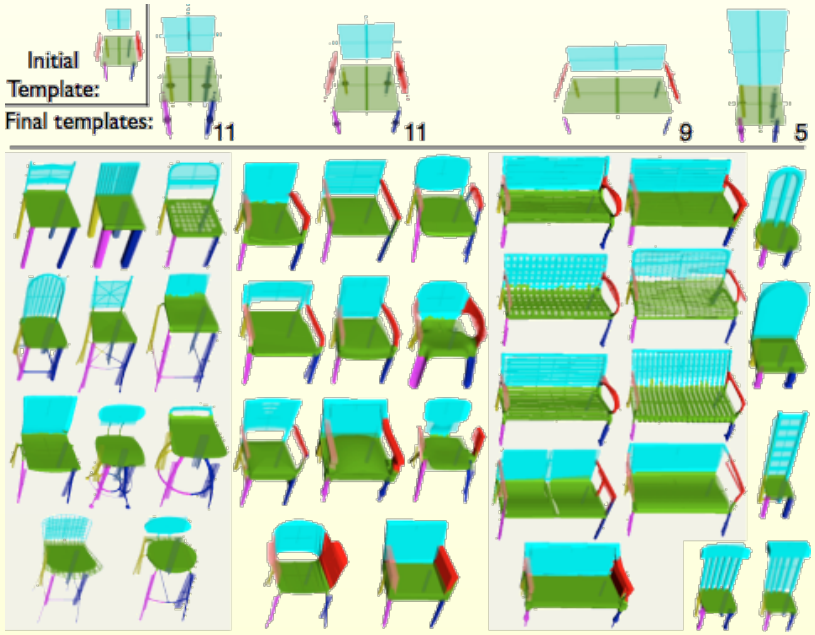
$$\max_{S_1,S_2} \text{score}(S_1)+\text{score}(S_2)+\text{consistency}(S_1,S_2)$$

- Outline
  - Segmentation parameterization
  - Segmentation score
  - Consistency score
  - 0-1 linear programming formulatio



# Learning part-based templates

- **"Learning Part-based Templates from Large Collections of 3D Shapes"** [Kim et al. 2013]
  - Jointly solve for deformations, part segmentation and inter-model correspondence

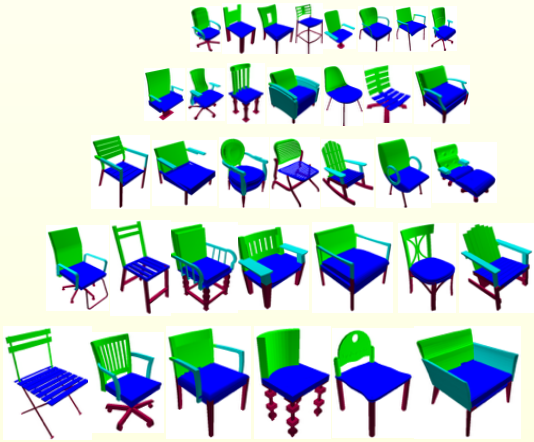


Semi-supervised segmentation

# ACTIVE LEARNING WITH HUMAN IN THE LOOP

# Active segmentation learning

- Data-driven method perform well when
  - They rely on big datasets
  - With detailed annotations (e.g., parts labels)
  - Annotations are curated



- Manual annotation
  - Time consuming
  - Not suitable for large collections
- Automatic annotation
  - Never perfectly reliable

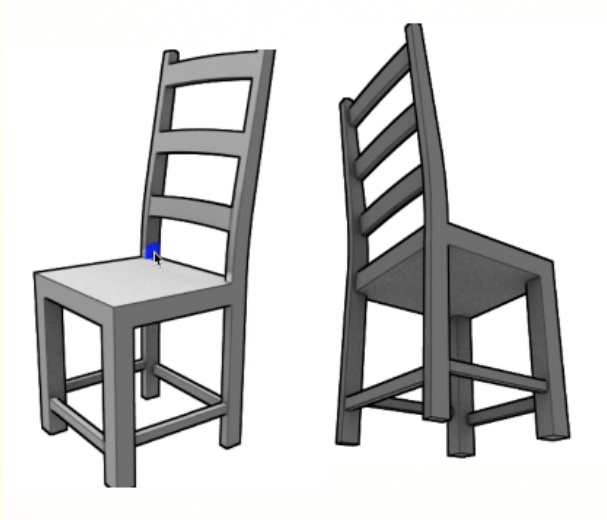
# Manual Annotation

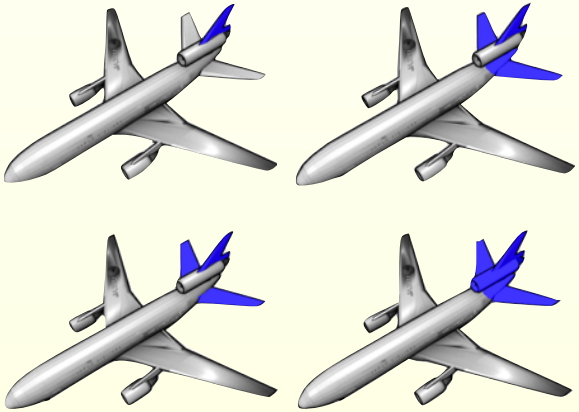
**Time consuming**

**Low efficiency**

**Not satisfactory accuracy**

Airplane tail





- *Millions of 3D models*
- *Constantly evolving*

- *3D annotation takes lots of time*

- *Semantic ambiguity*

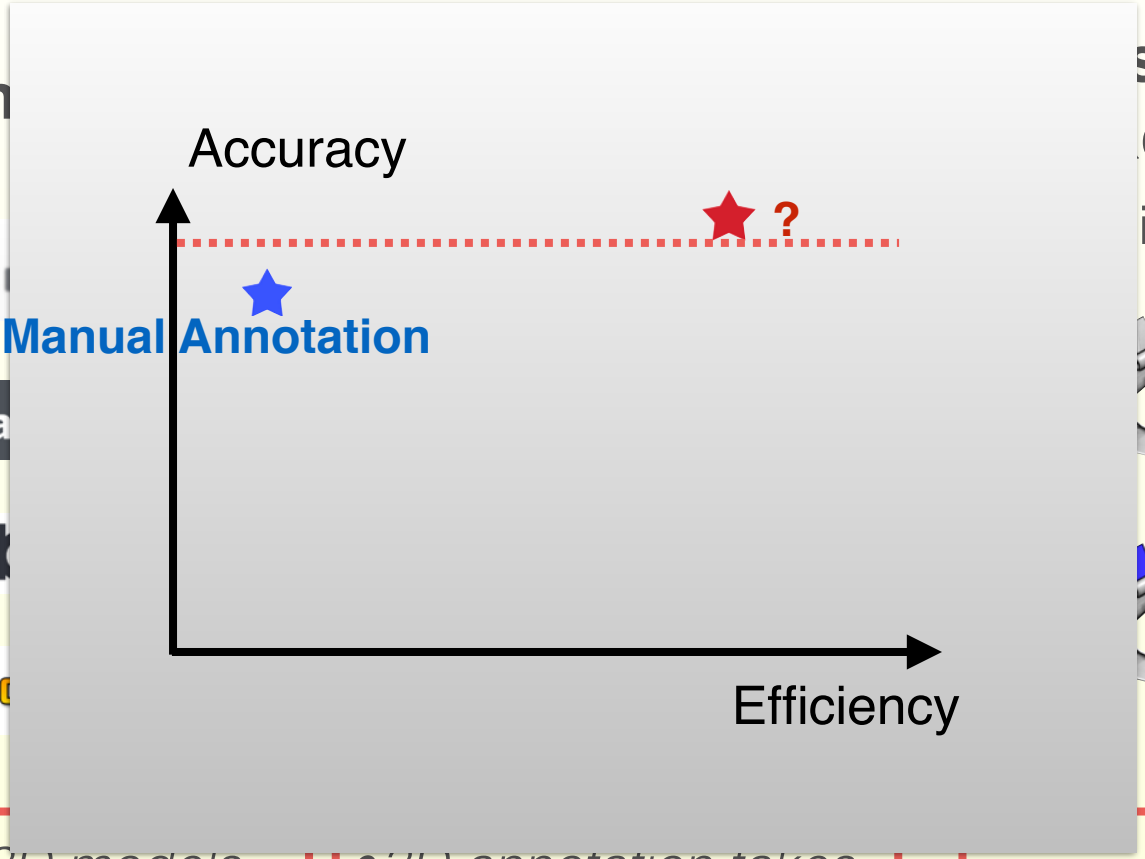
Slide credit: L. Yi

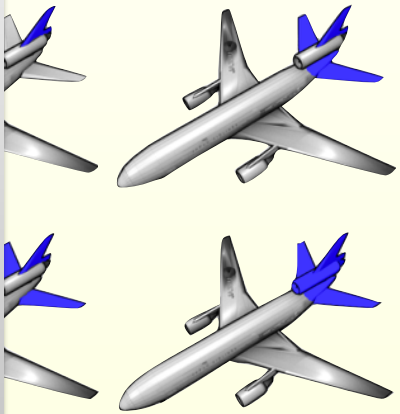
# Manual Annotation

Time con

satisfactory
ccuracy

irplane tail



- *Millions of 3D models*
- *Constantly evolving*

- *3D annotation takes lots of time*

- *Semantic ambiguity*

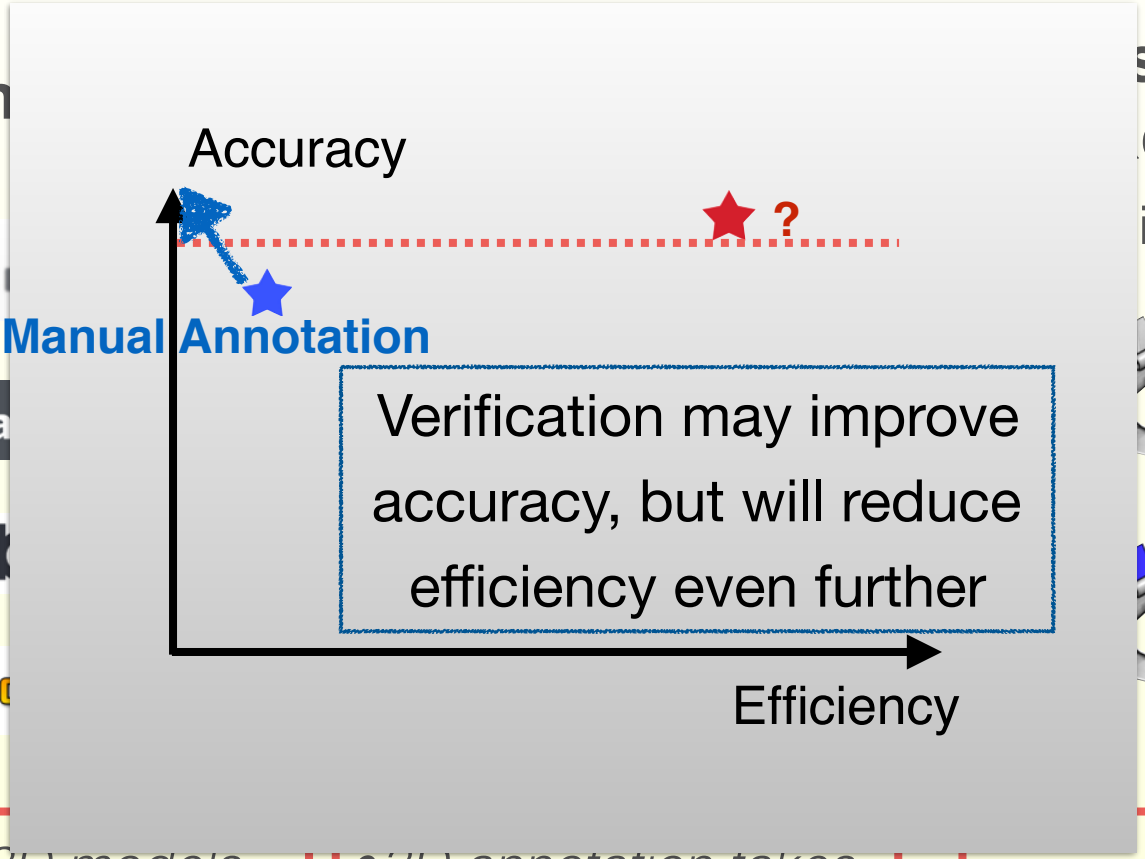
Slide credit: L. Yi

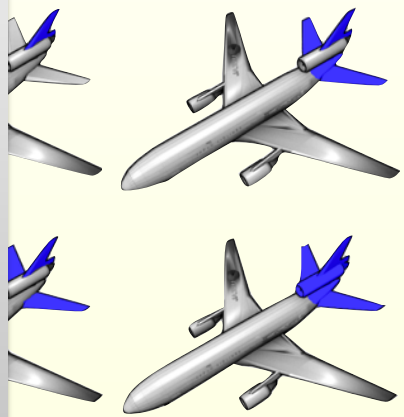
# Manual Annotation

**Time con**

**satisfactory**
**ccuracy**

irplane tail



- *Millions of 3D models*
- *Constantly evolving*

- *3D annotation takes lots of time*

- *Semantic ambiguity*

Slide credit: L. Yi

# Automatic annotation

Slide credit: L. Yi

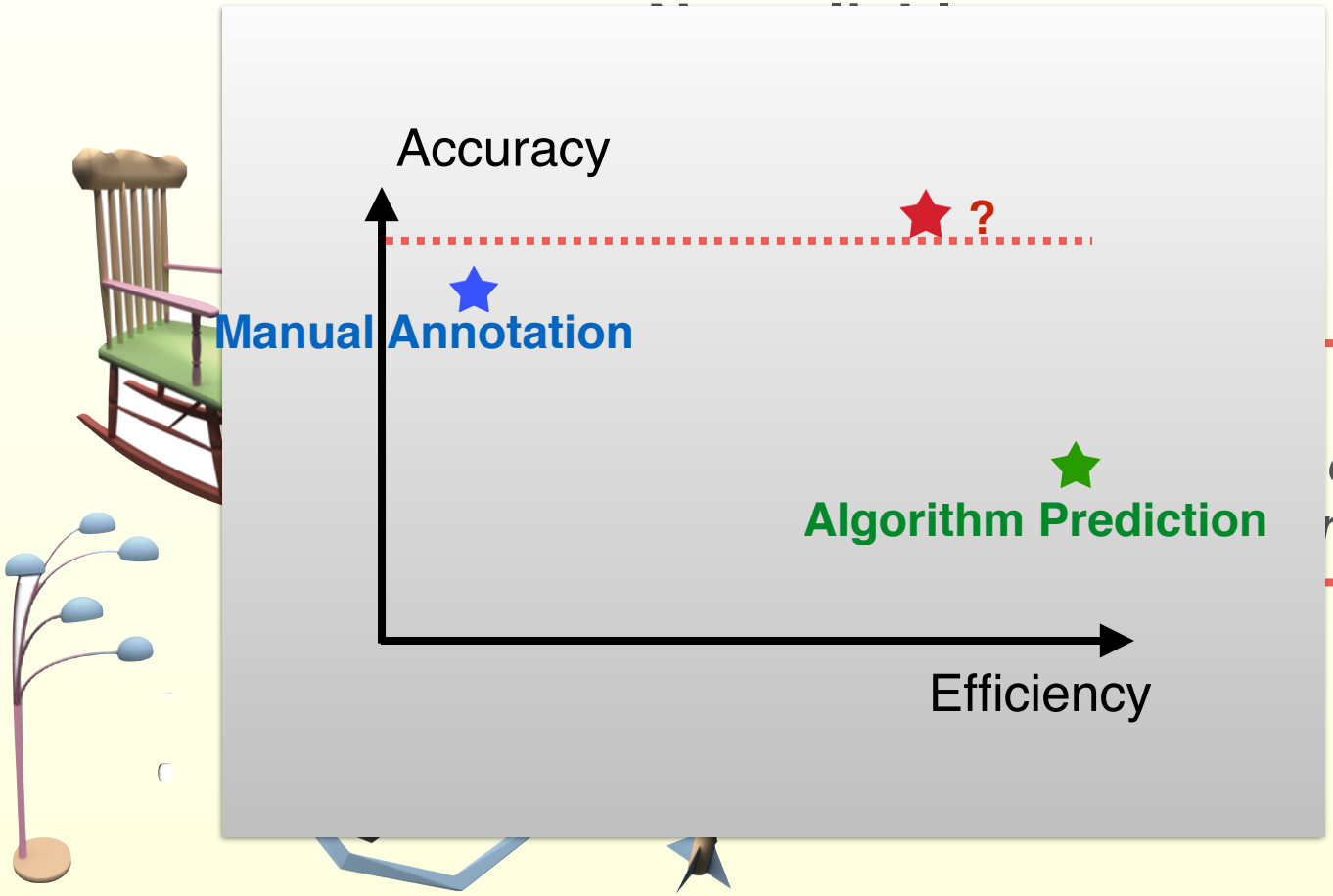
# Automatic annotation

**Not reliable**

- ***Large variation***
- ***Different levels of semantic knowledge are needed***

Slide credit: L. Yi

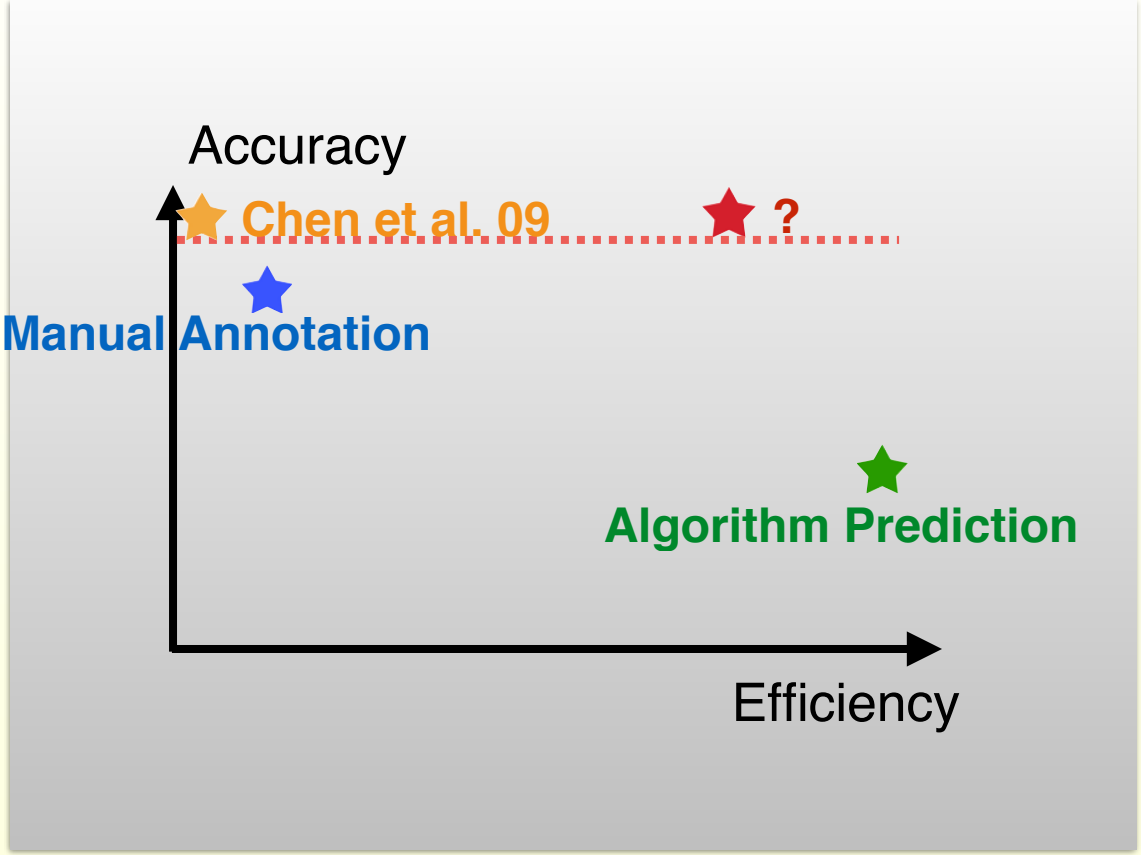
# Automatic annotation




*of semantic*
*needed*

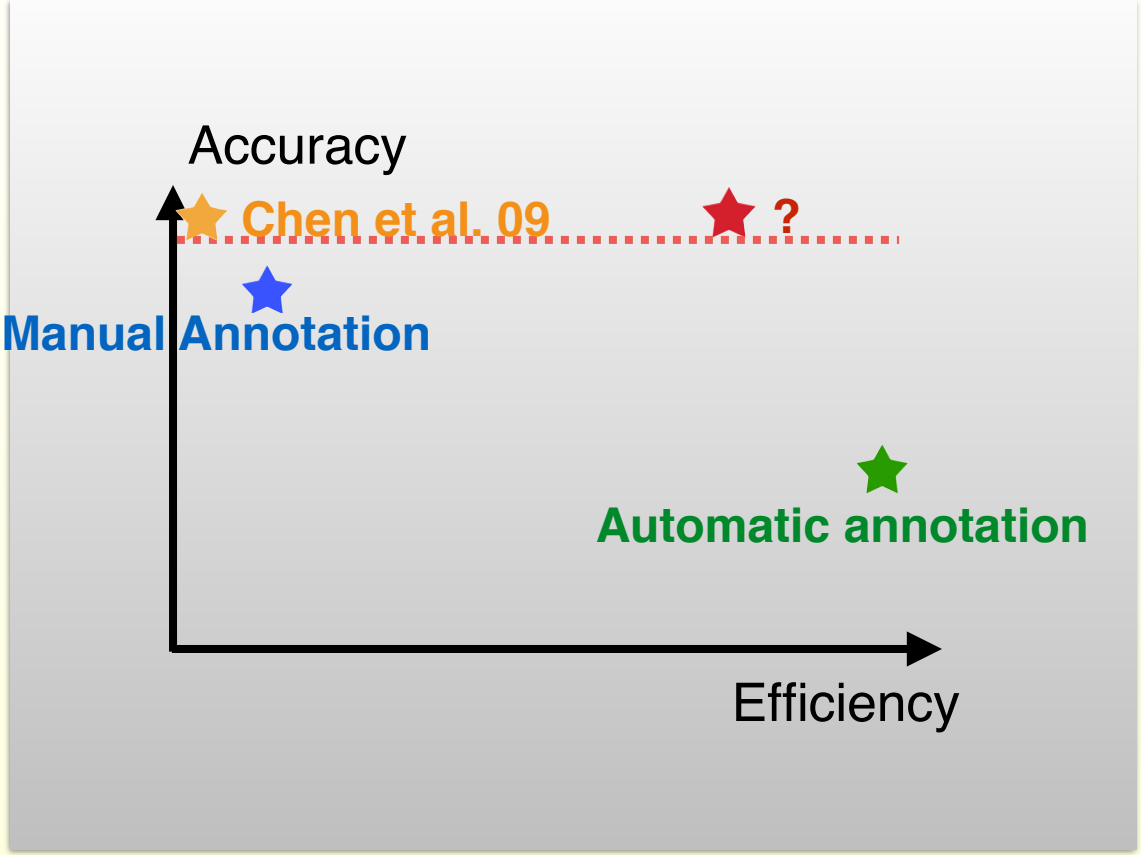
Slide credit: L. Yi

# Automatic annotation



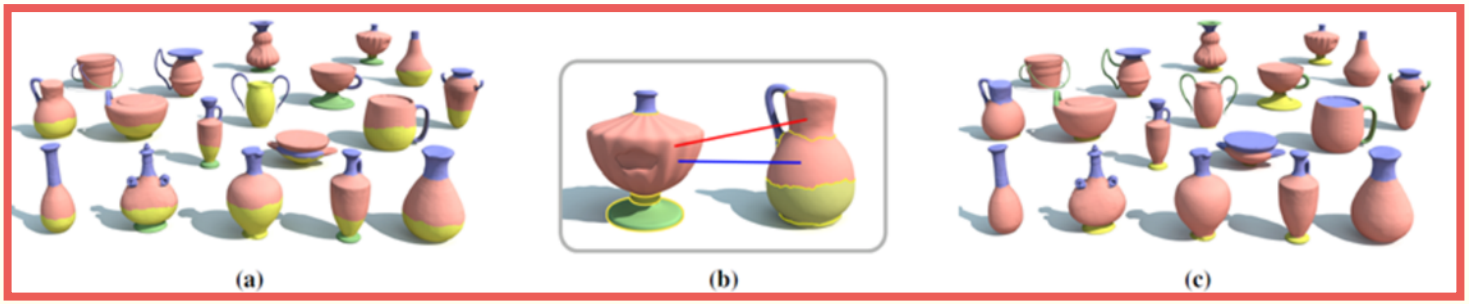

Slide credit: L. Yi

# Automatic annotation

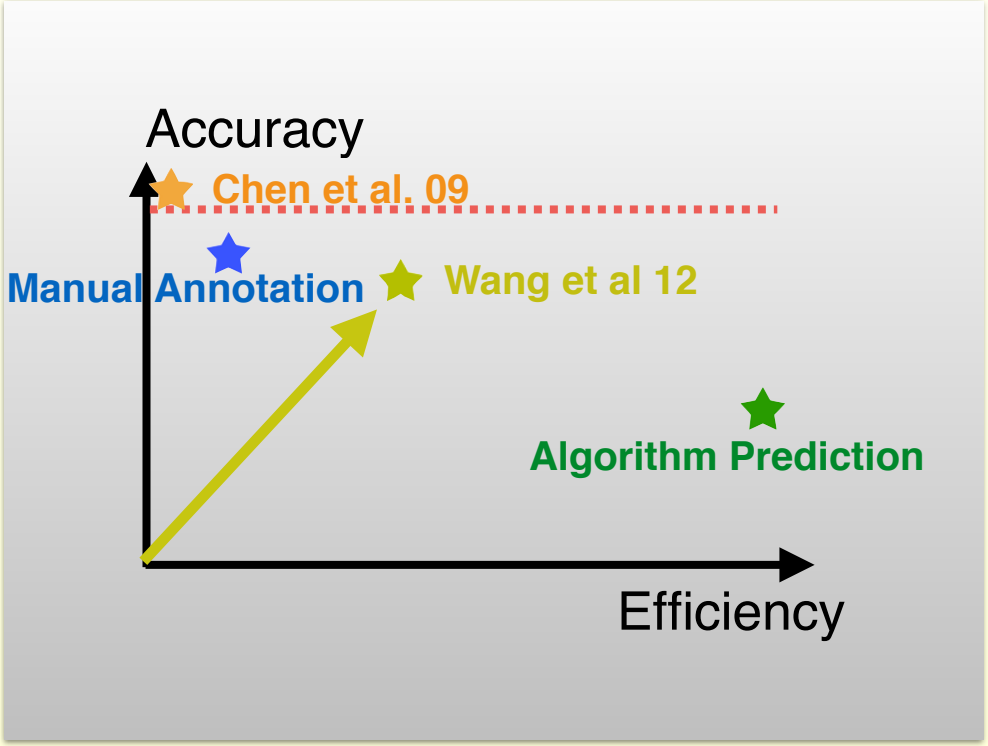



Slide credit: L. Yi

# Problem Definition



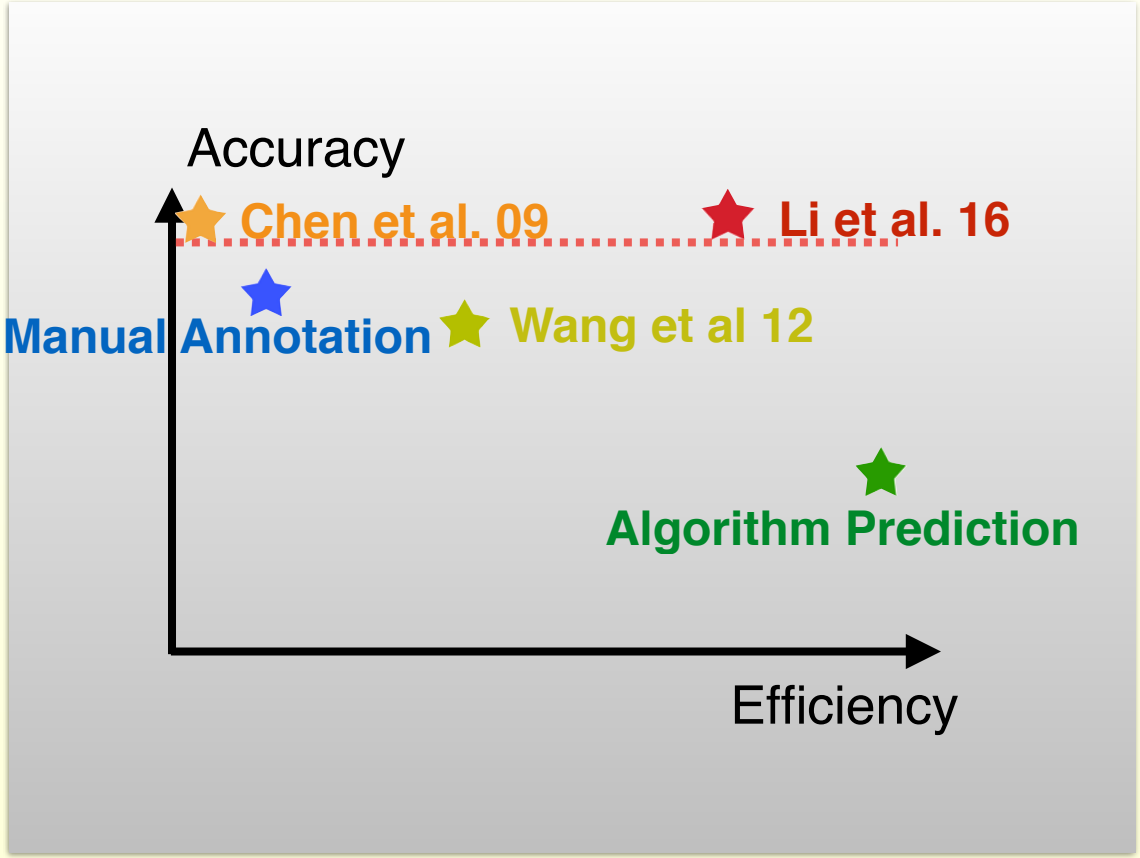

Active Co-Analysis of a Set of Shapes [Wang et al. 12]




Slide credit: L. Yi

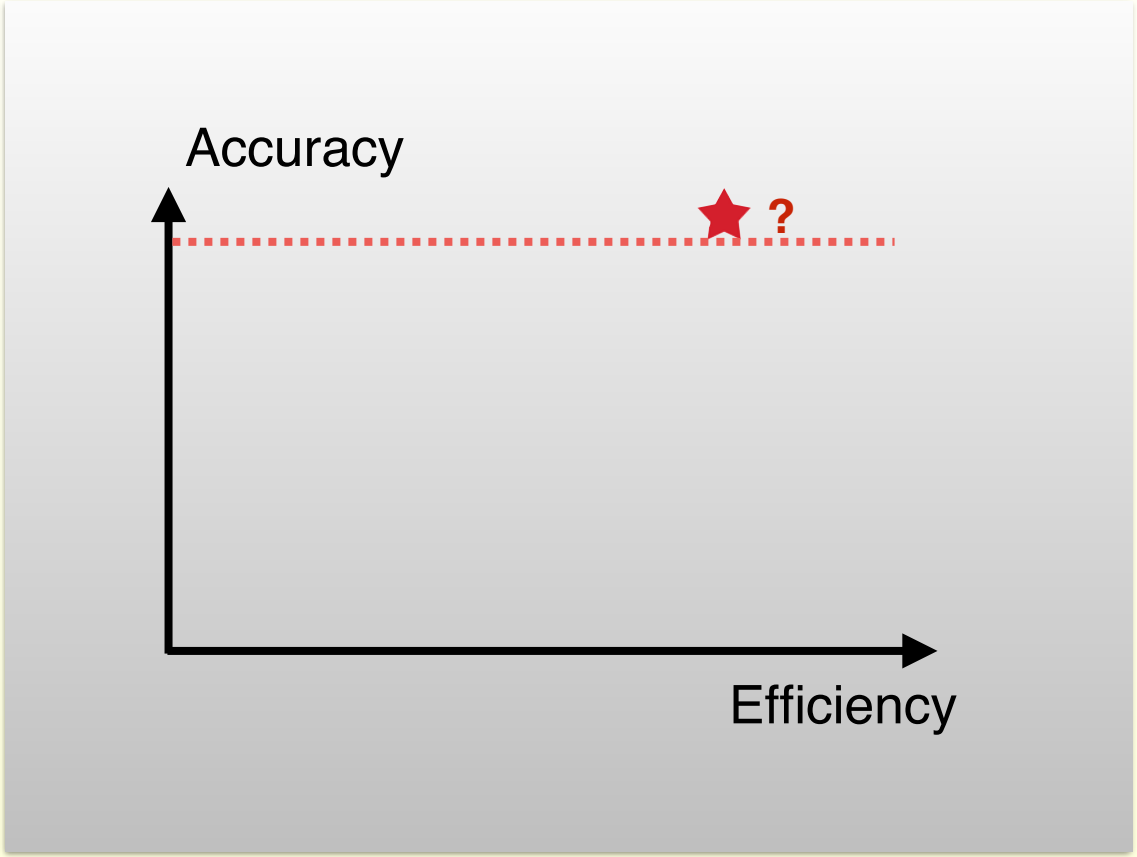
# Problem Definition

- **"A Scalable Active Framework for Region Annotation in 3D Shape Collections"** [Li et al. 2016]



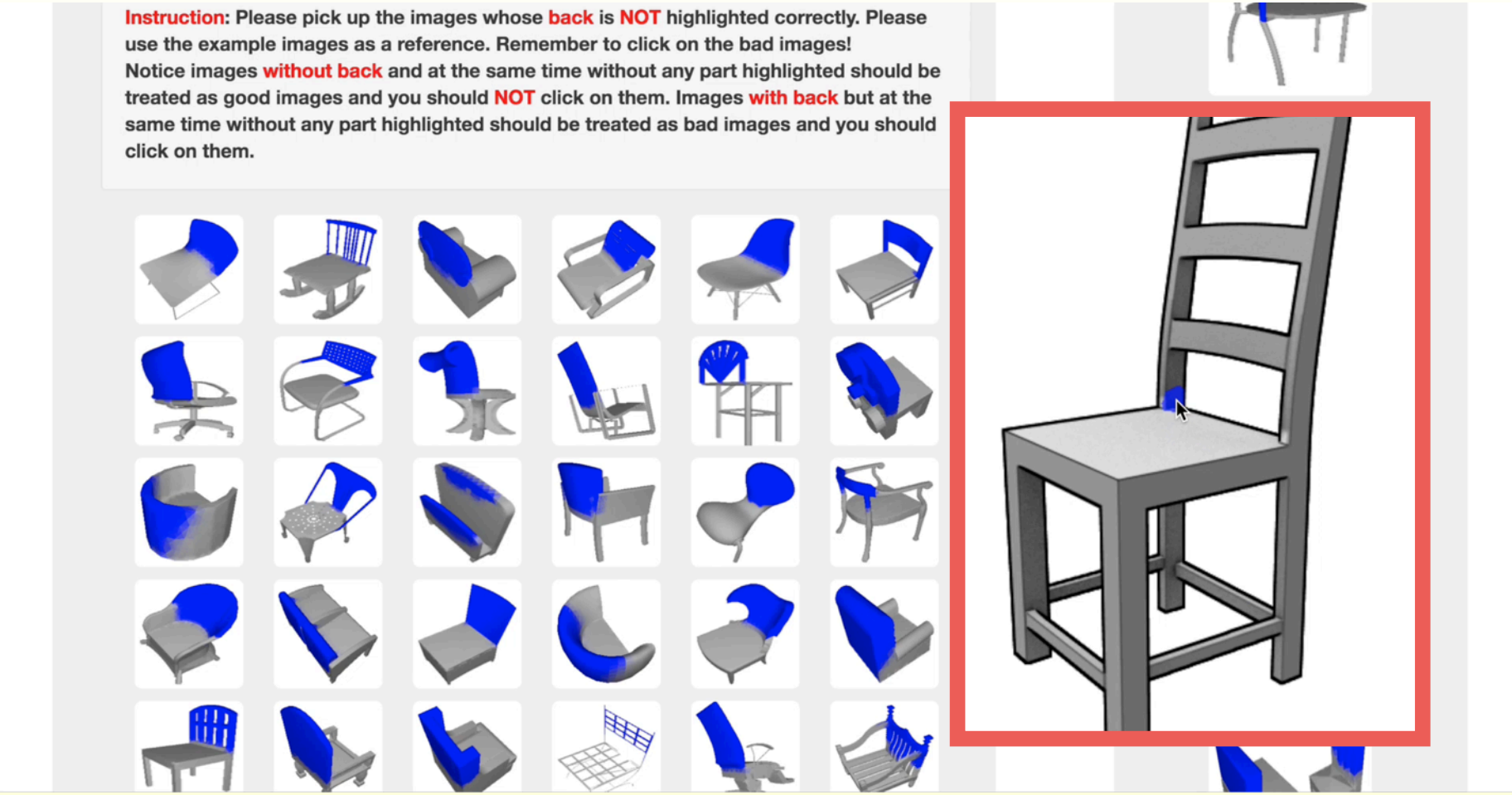

Slide credit: L. Yi

# Problem Definition




Slide credit: L. Yi

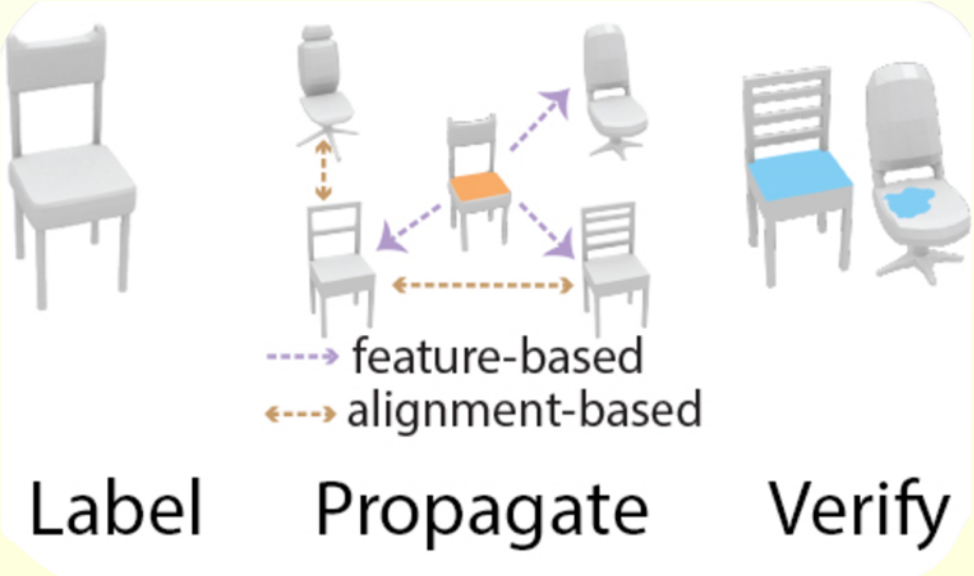
# Main idea: verification is much more efficient than labeling




Slide credit: L. Yi

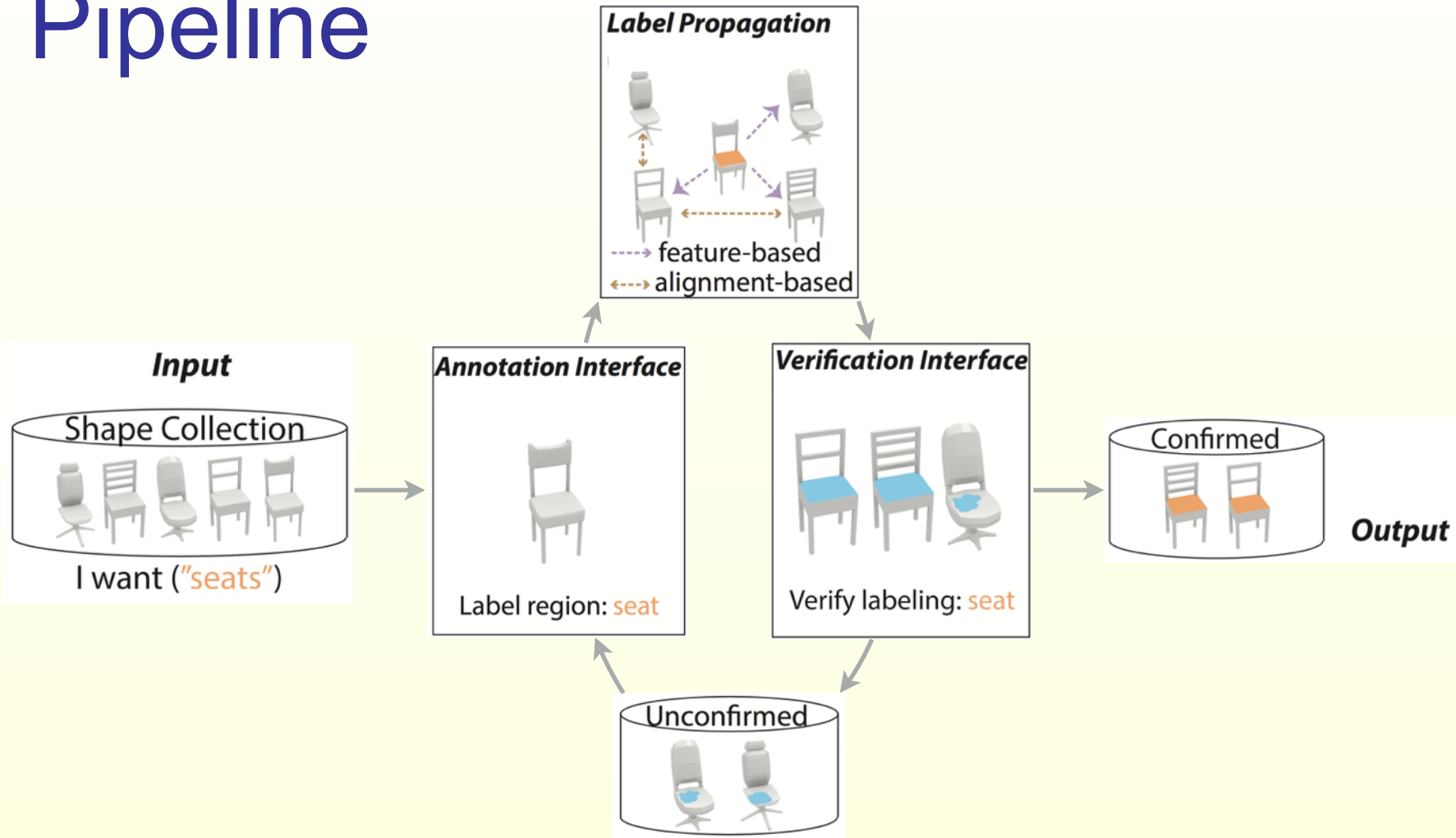
# Approach overview

- Unified framework which combines
  - human annotation
  - automatic prediction by correspondence propagation
  - batch verification by expert



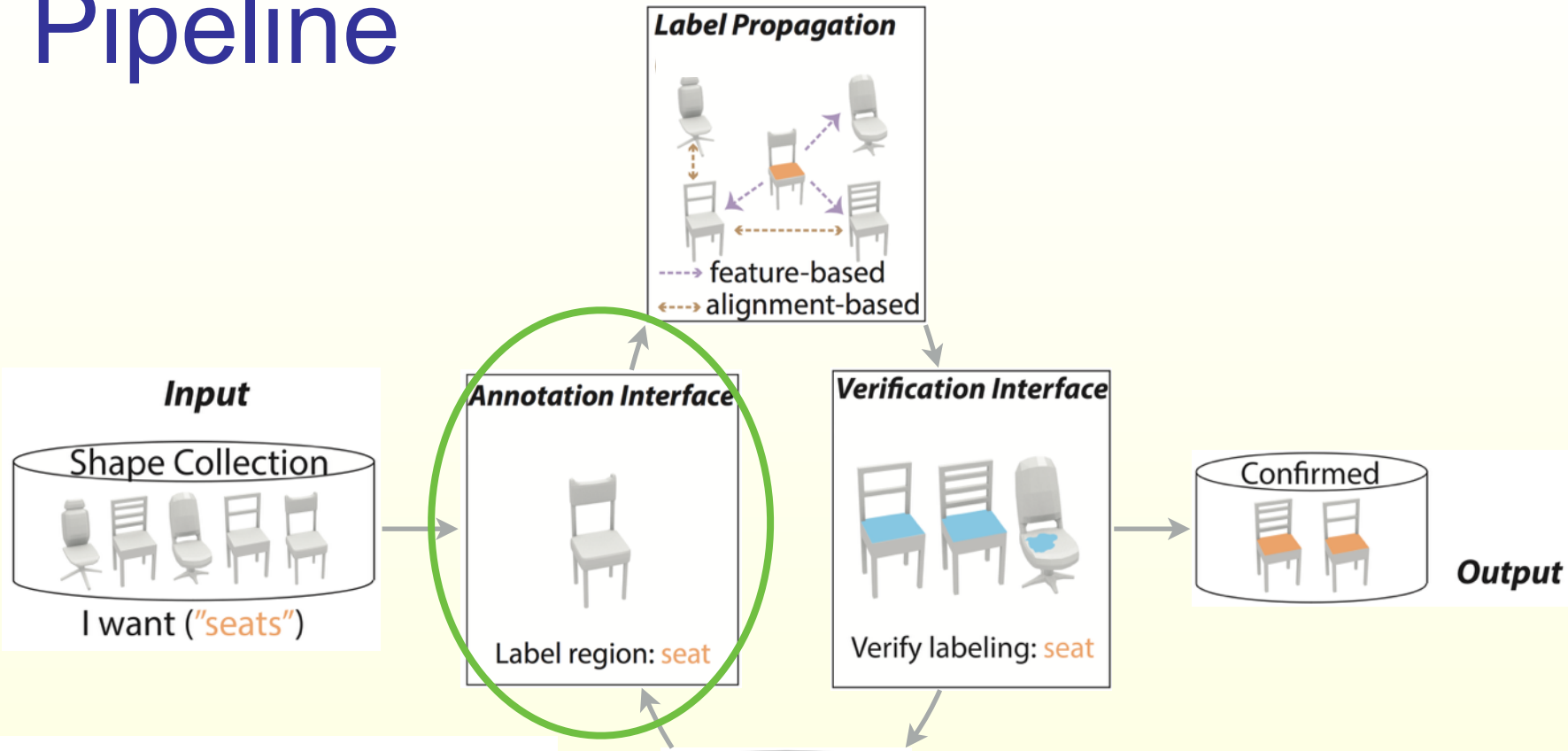

Slide credit: L. Yi

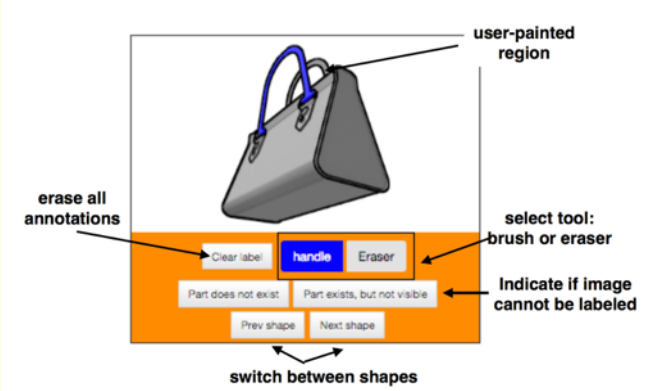
# Pipeline




Slide credit: L. Yi

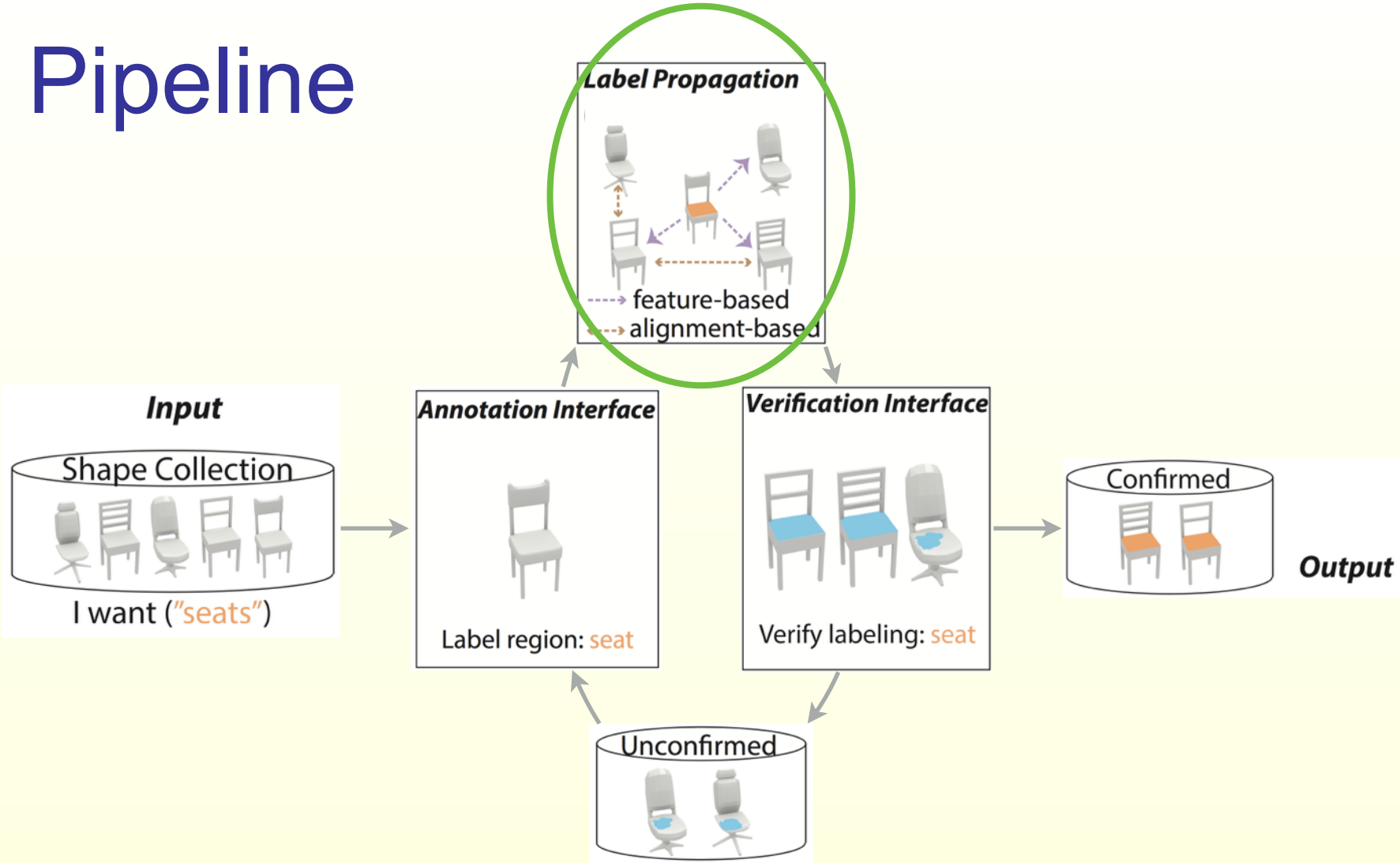
# Pipeline



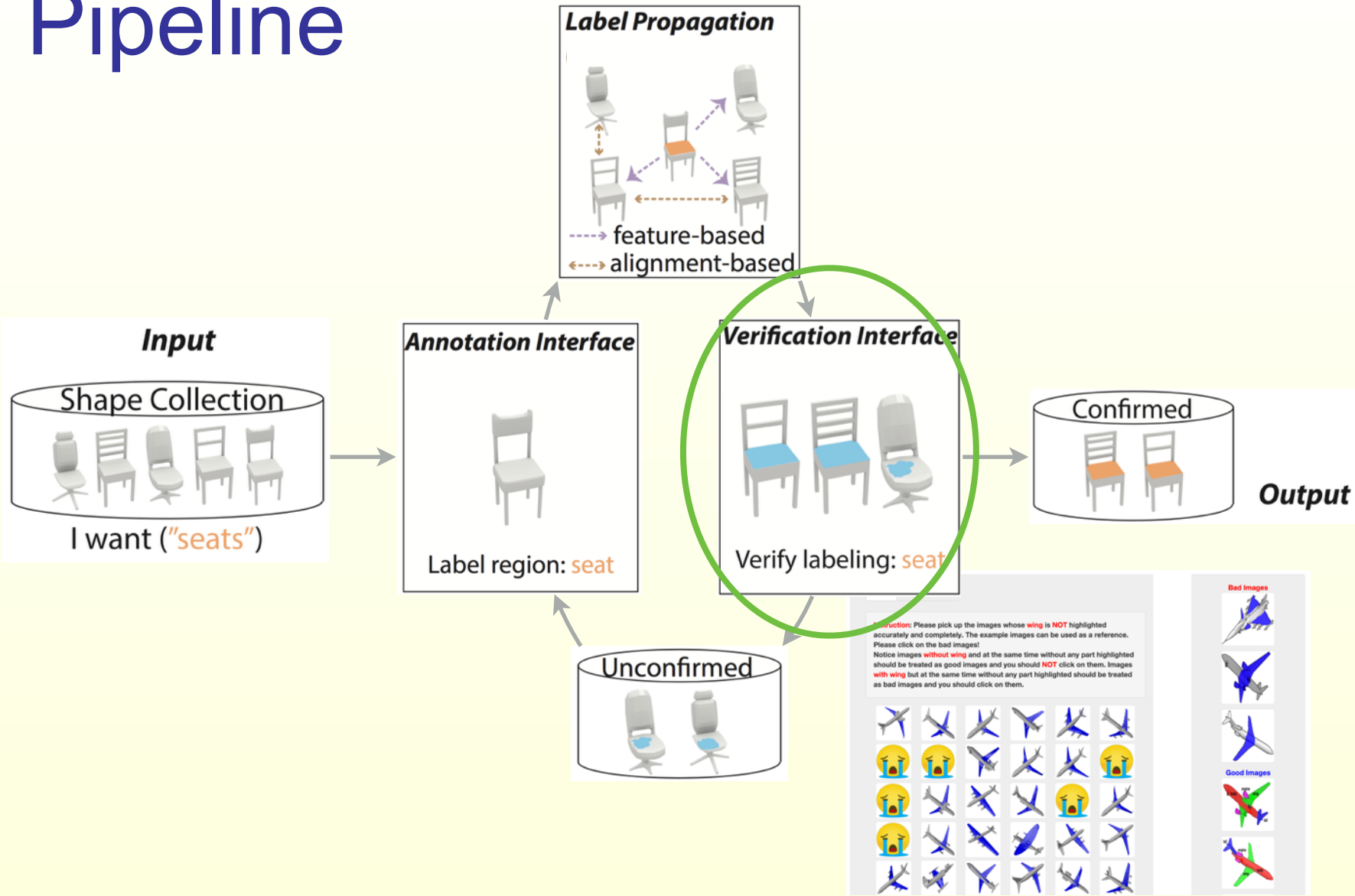

Slide credit: L. Yi

# Pipeline



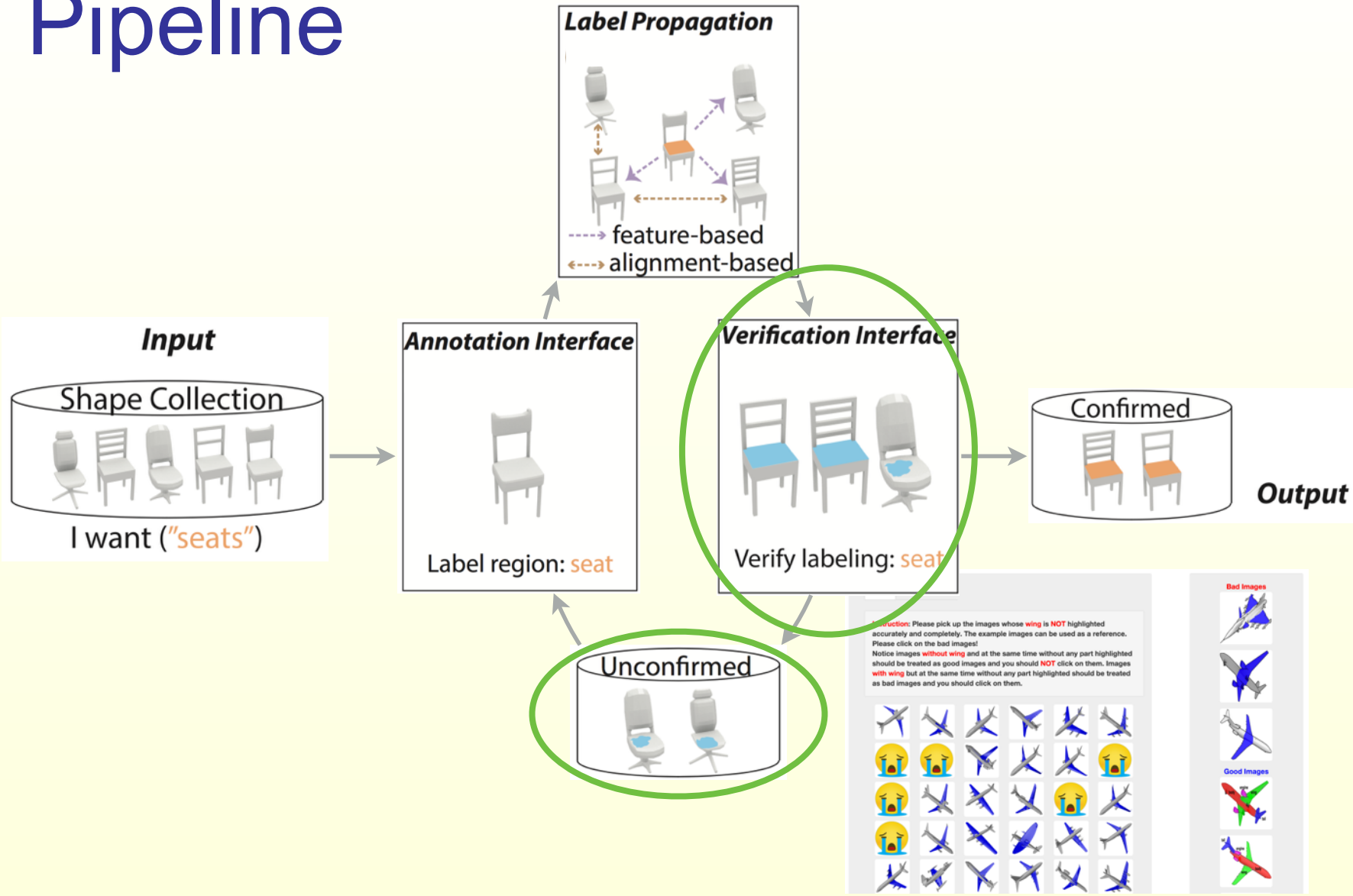

Slide credit: L. Yi

# Pipeline



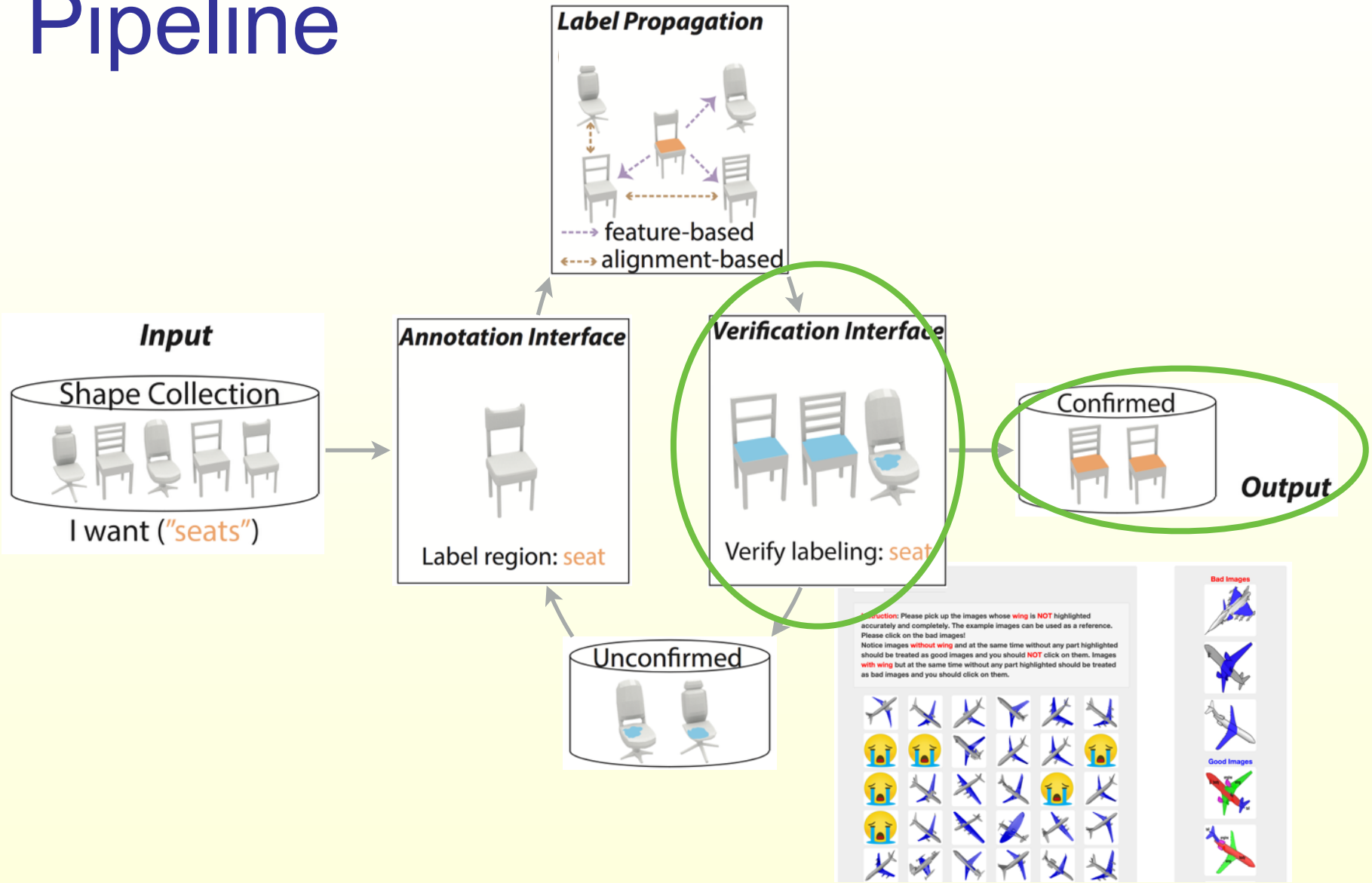

Slide credit: L. Yi

# Pipeline



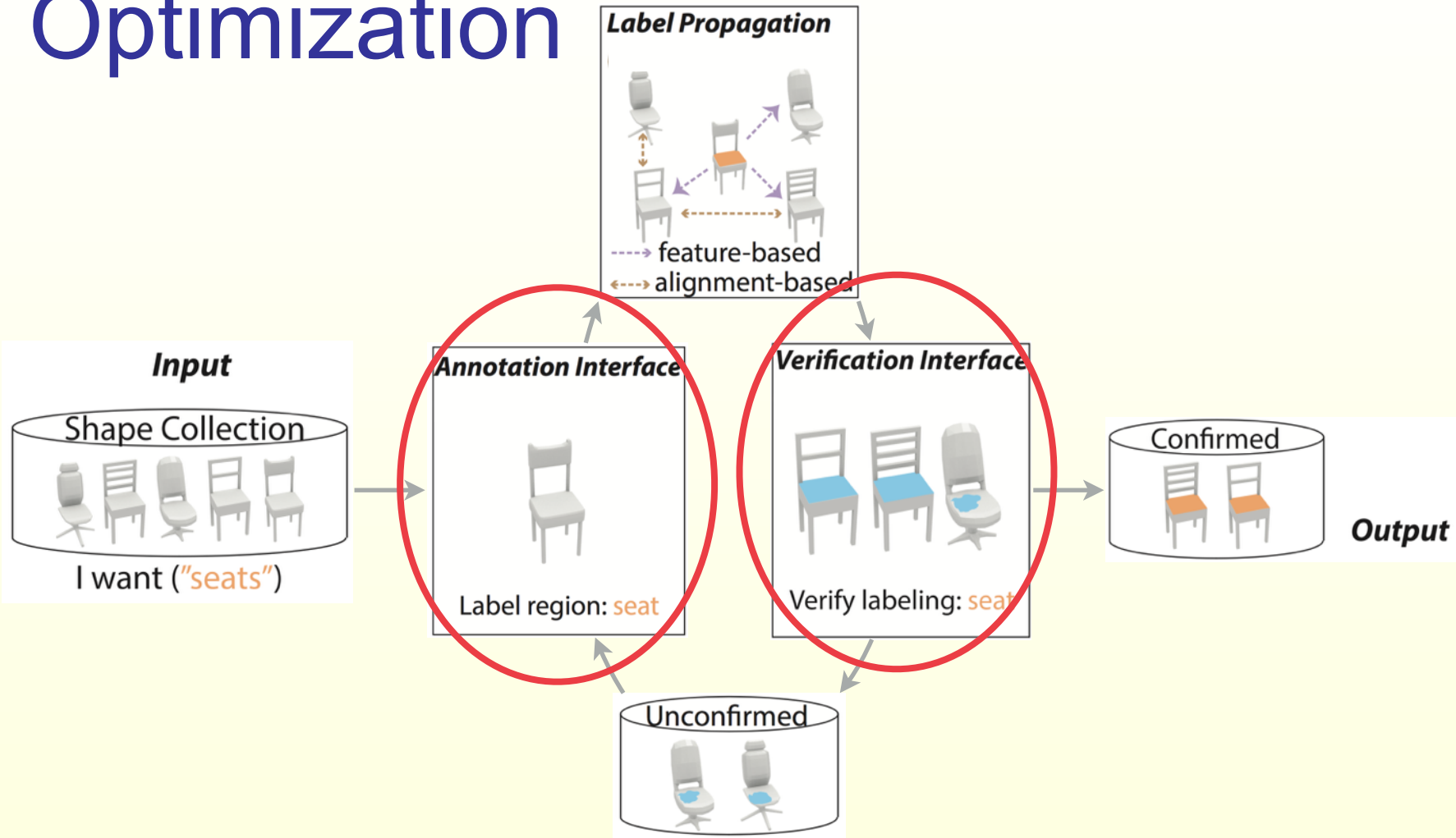

Slide credit: L. Yi

# Pipeline



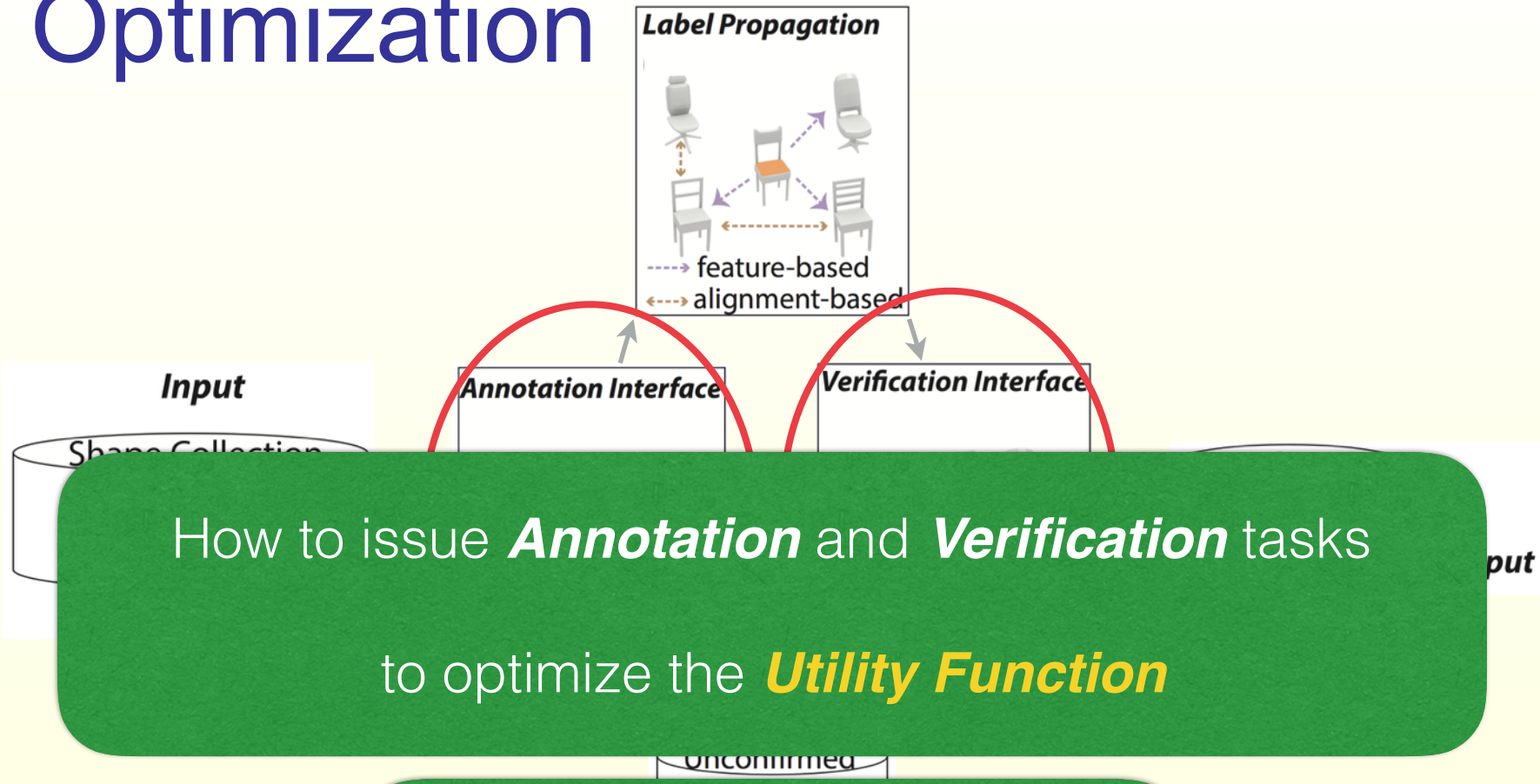

Slide credit: L. Yi

# Optimization




Slide credit: L. Yi

# Optimization



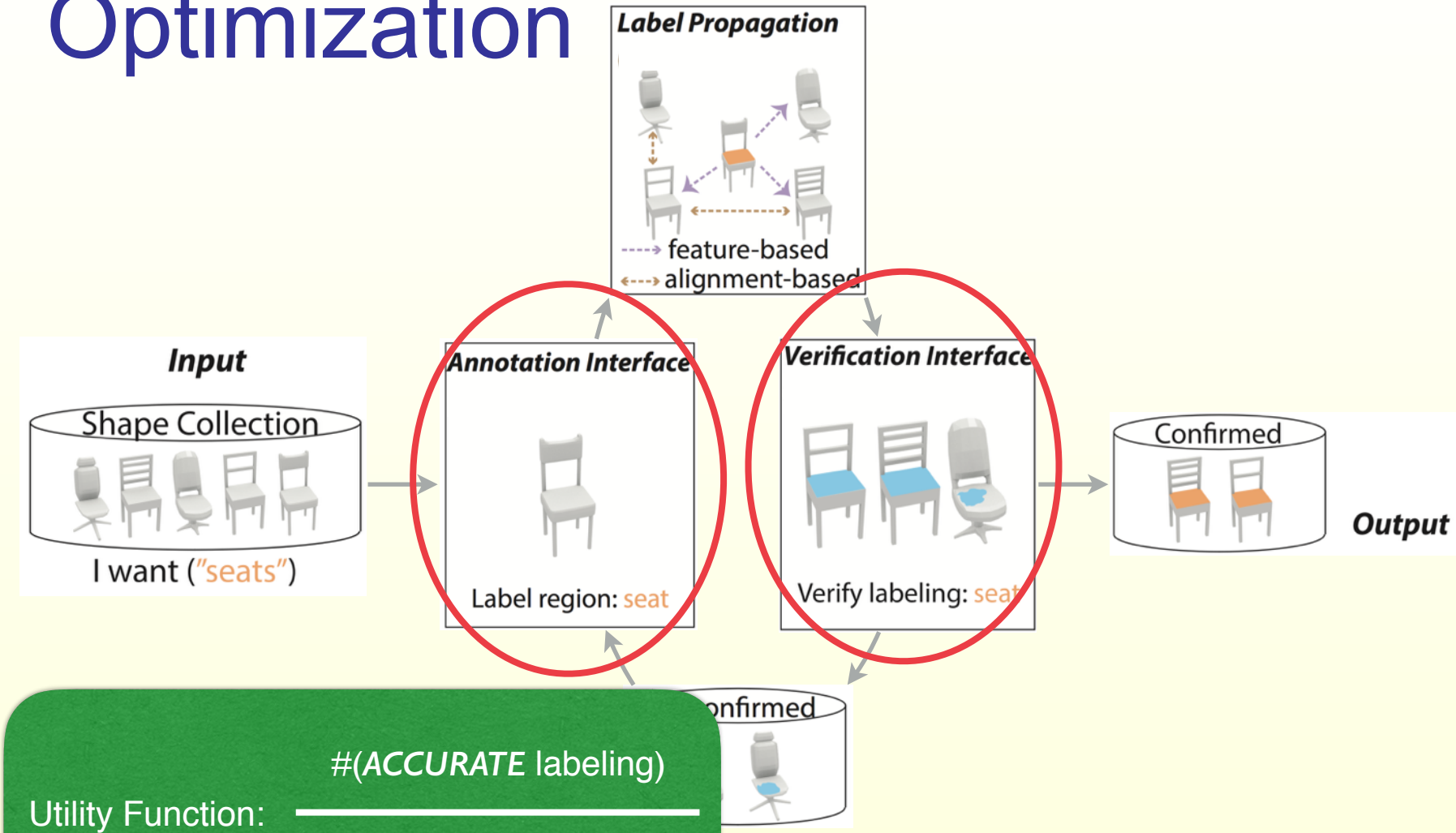

How to issue ***Annotation*** and ***Verification*** tasks

to optimize the ***Utility Function***

Utility Function: $\dfrac{\#(\textit{ACCURATE}\text{ labeling})}{\text{worker time}}$

Slide credit: L. Yi

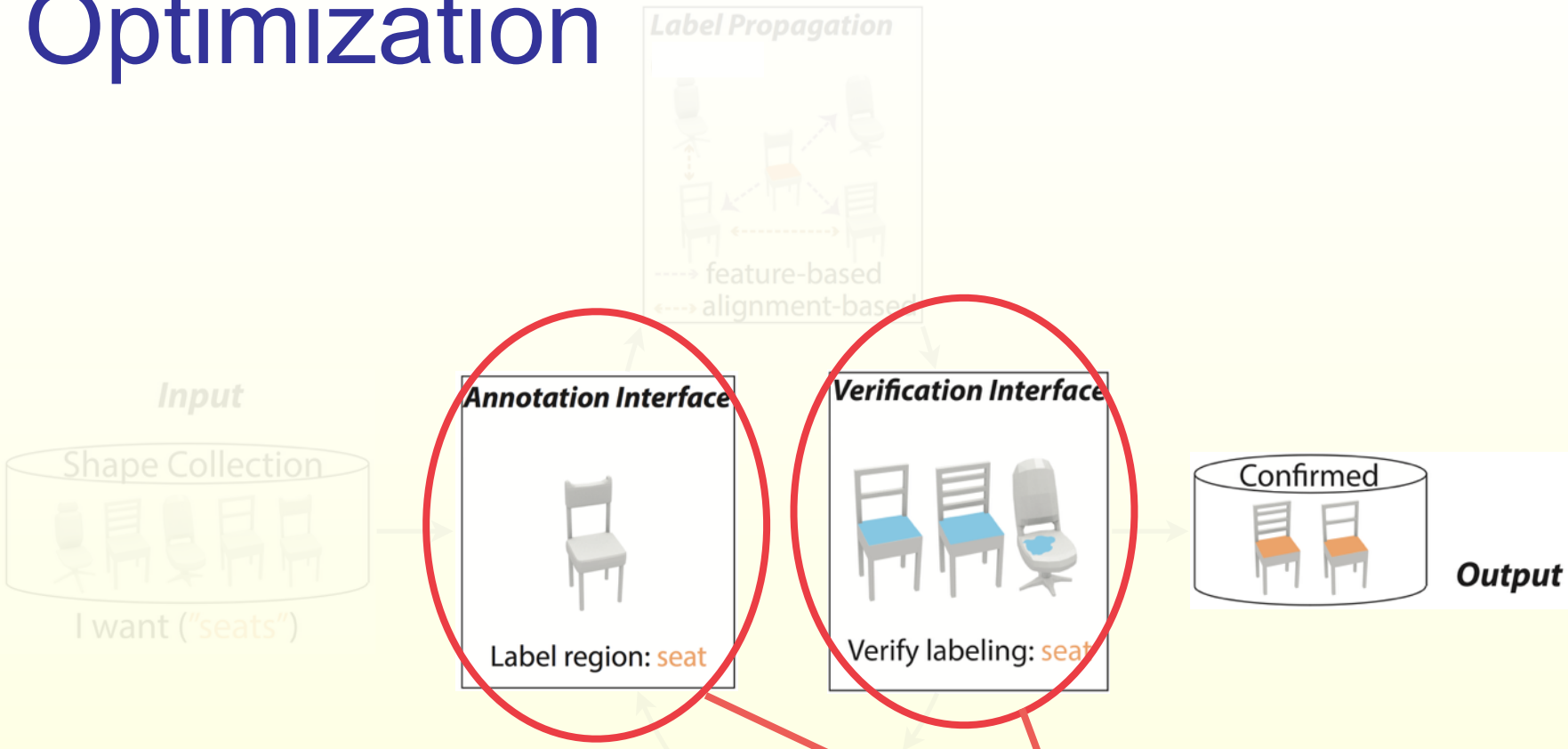
# Optimization




Utility Function: $\frac{\#(\textit{ACCURATE}\text{ labeling})}{\text{worker time}}$

Slide credit: L. Yi

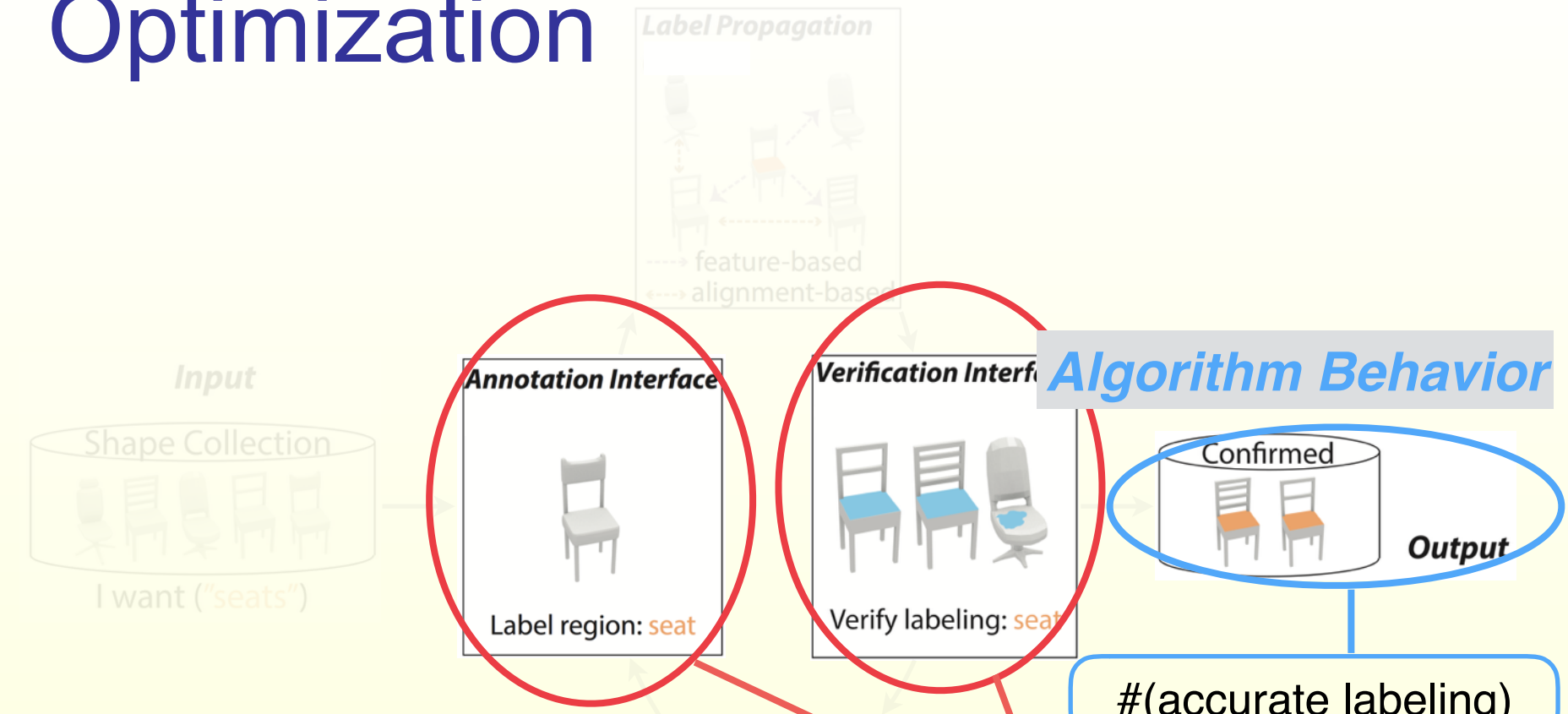
# Optimization




$$\text{Utility Function: } \frac{\#(\textit{ACCURATE}\text{ labeling})}{\text{worker time}}$$

worker time

# Optimization




Utility Function: $\frac{\#(\textit{ACCURATE}\text{ labeling})}{\text{worker time}}$

Slide credit: L. Yi

# Utility Function

Annotation, verification sets

$$\underset{\mathcal{A},\mathcal{V}}{\operatorname{argmin}} \frac{\mathbb{E}[N_{\text{good}}]}{\mathbb{E}[T]}$$

# accurate labels expectation

Worker time expectation

Select Annotation Set: ***Beam Search***

Slide credit: L. Yi

# Utility Function

Annotation, verification sets

$$\underset{\mathcal{A},\mathcal{V}}{\operatorname{argmin}} \frac{\mathbb{E}[N_{\text{good}}]}{\mathbb{E}[T]}$$

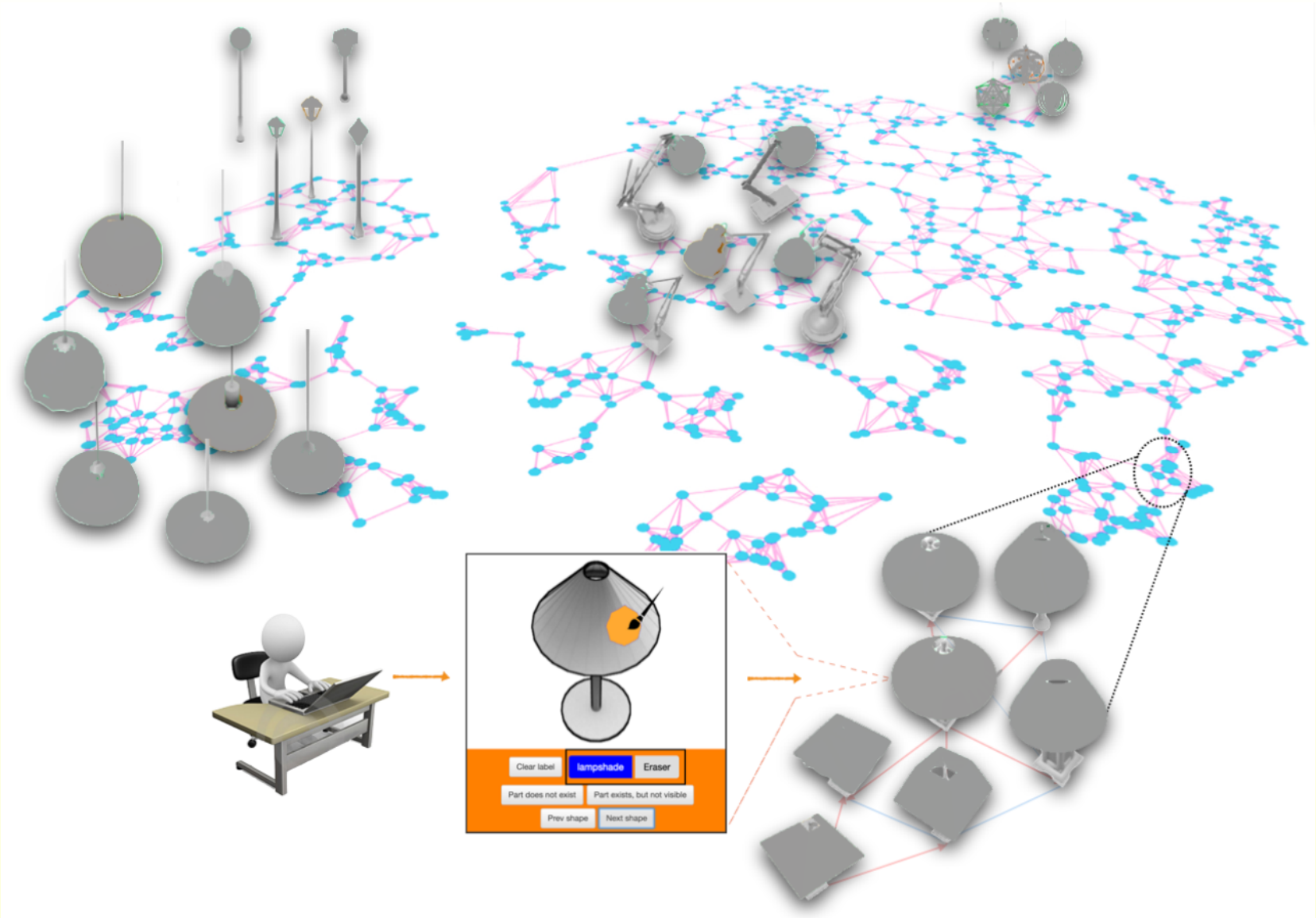
# accurate labels expectation

Worker time expectation

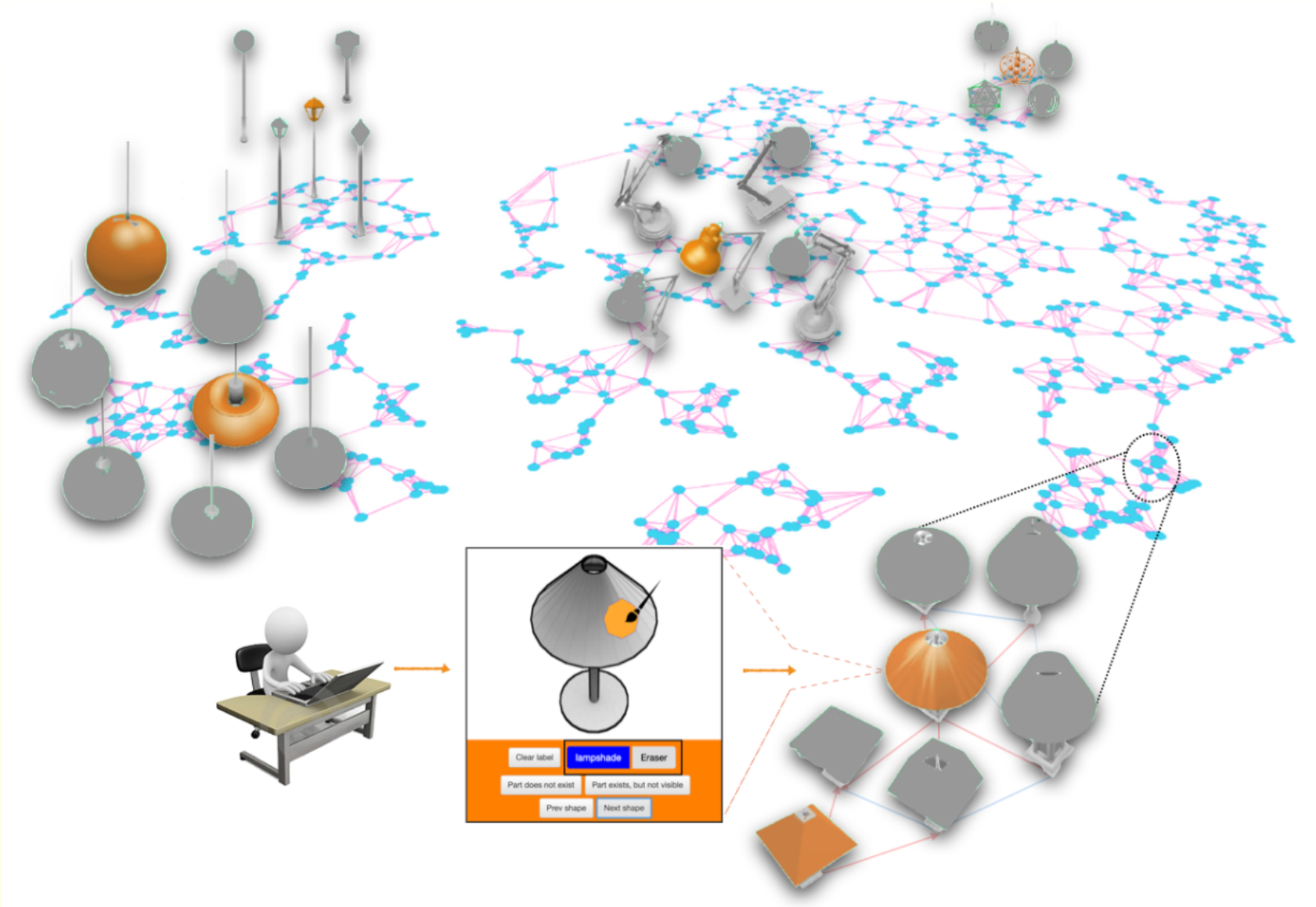
Select Annotation Set: ***Beam Search***

Select Verification Set: ***Greedy Search***

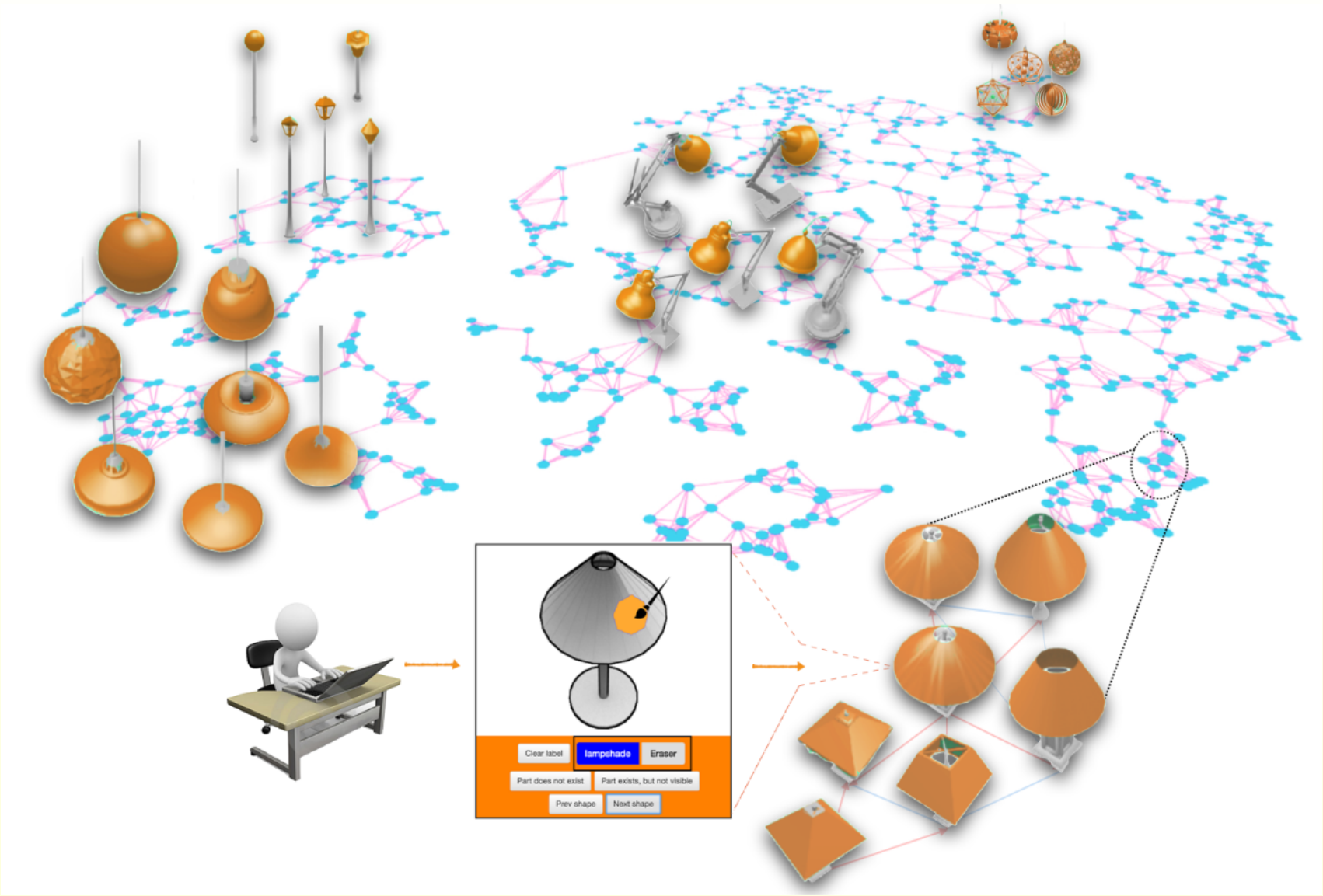
Slide credit: L. Yi



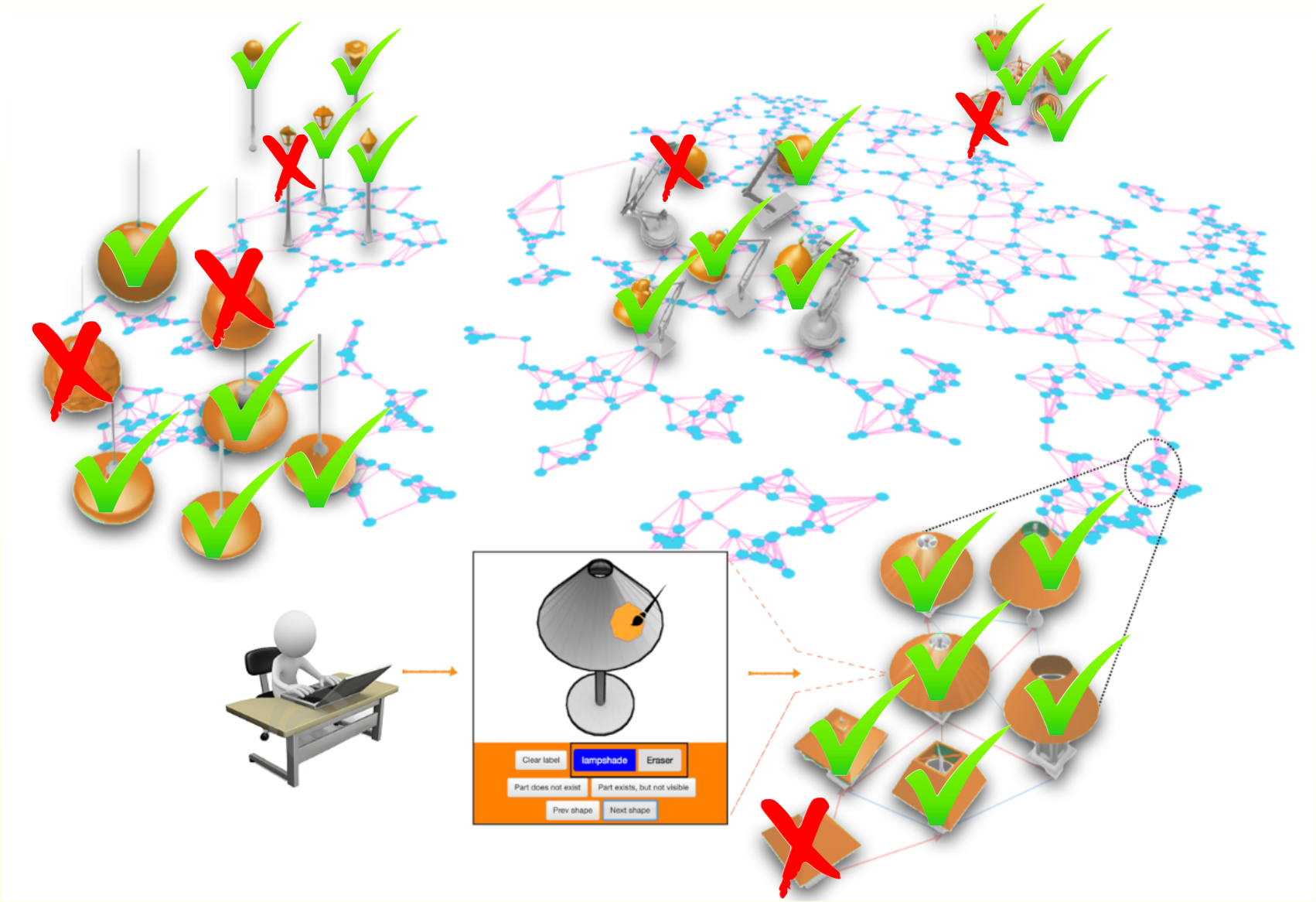

Slide credit: L. Yi



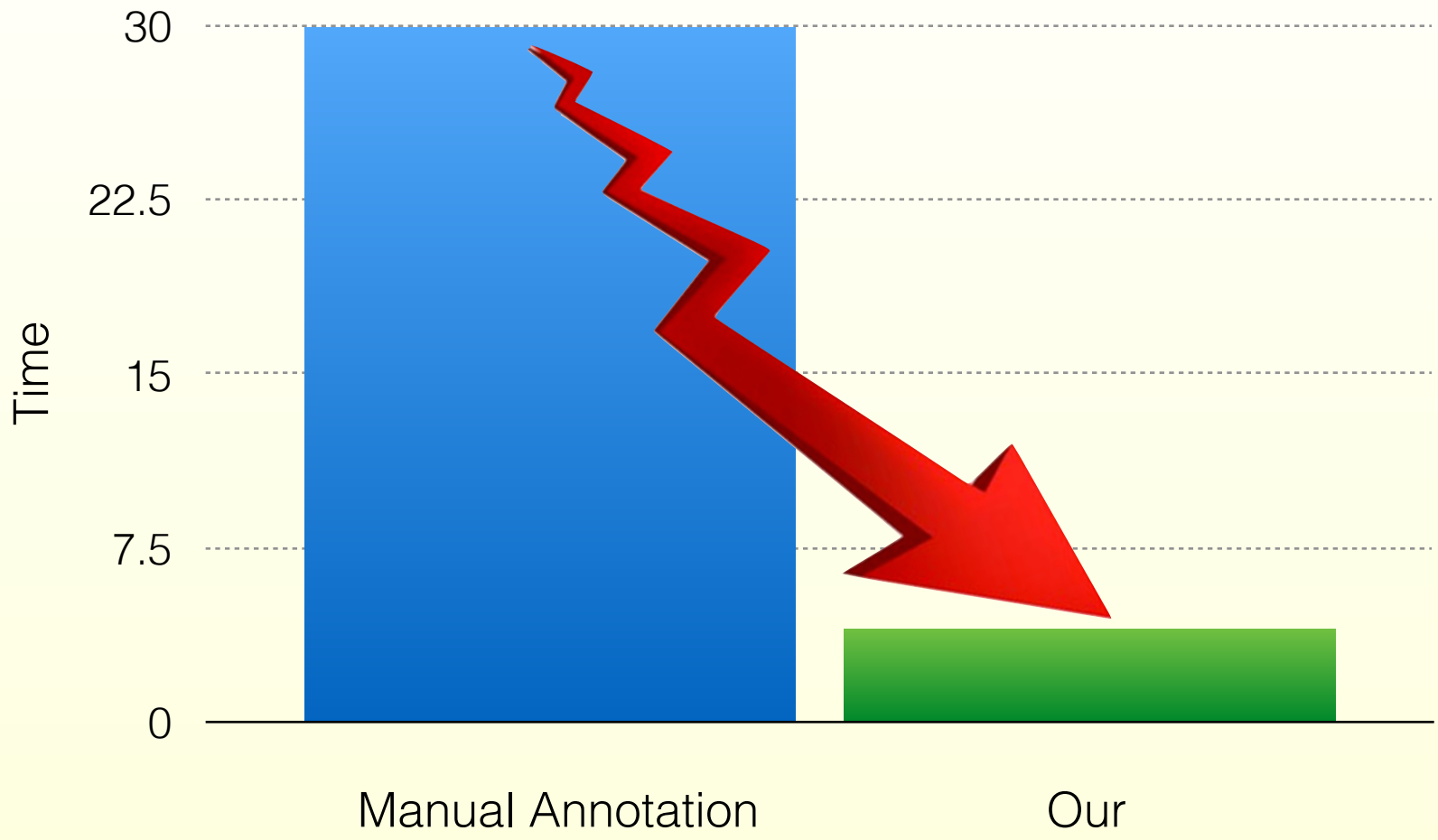

Slide credit: L. Yi




Slide credit: L. Yi

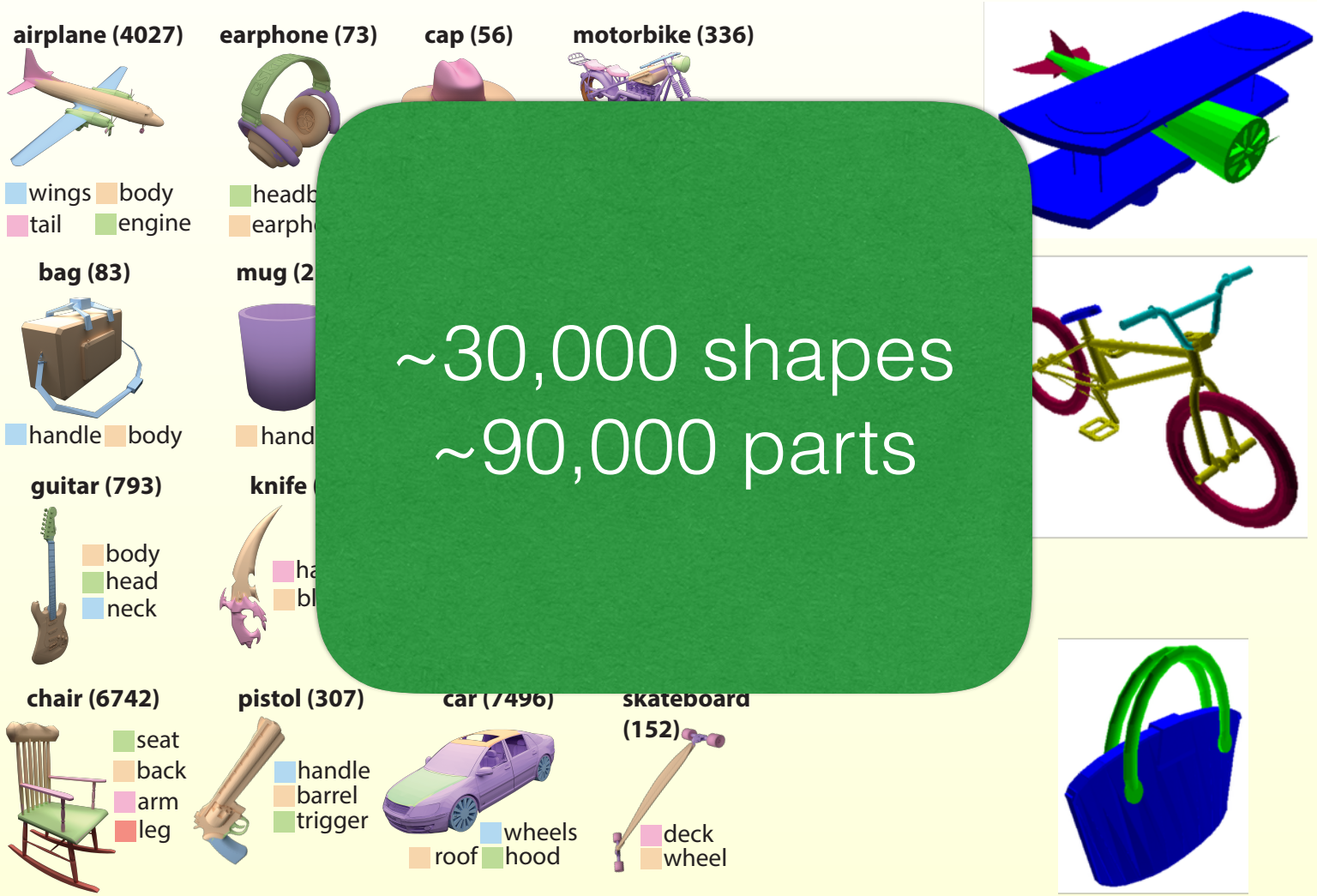



Slide credit: L. Yi




Slide credit: L. Yi

# Results




~30,000 shapes
~90,000 parts

Slide credit: L. Yi

# Evaluation

Part labeling on COSEG dataset [Wang et al. 12]

| #Mesh | Time ACA (min) | Time Ours (min) |
|---|---|---|
| 882 | 152.3 | 73.6 |

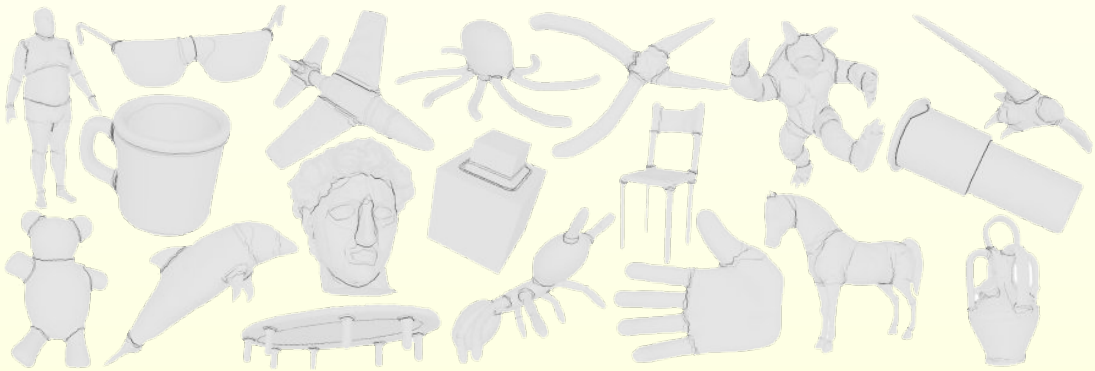
Slide credit: L. Yi

For your reference

# SEGMENTATION/LABELING DATASETS

# Segmentation/labeling datasets

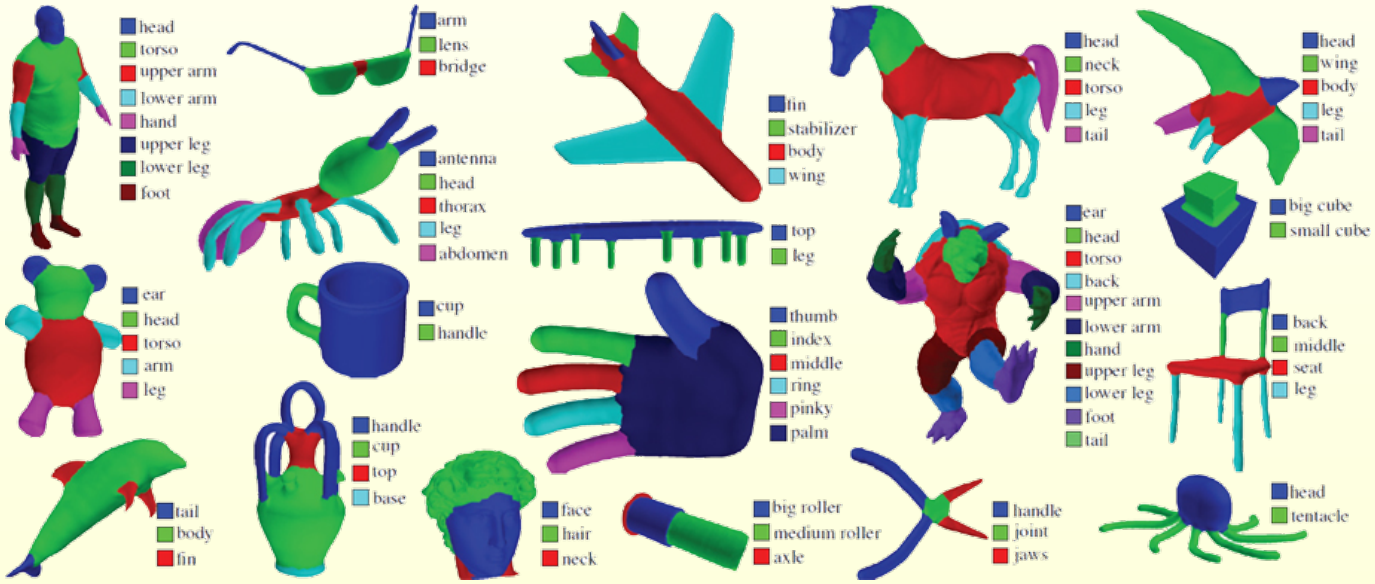
- Segmentation/labeling datasets links:
  - Princeton Segmentation Benchmark (PSB) [Chen et al. 2009] http://segeval.cs.princeton.edu



- 11 human generated segmentations (“probabilistic” ground truth)
  - 380 watertight meshes across 19 categories

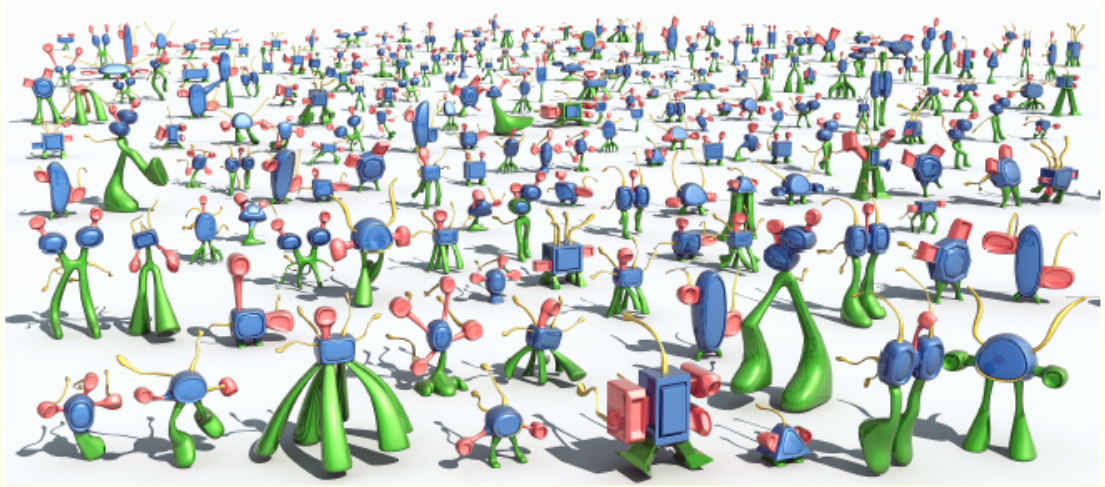
# Segmentation/labeling datasets

- Segmentation/labeling datasets links:
  - Labeled PSB dataset (L-PSB) [Kalogerakis et al. 2010] http://people.cs.umass.edu/%7Ekalo/papers/LabelMeshes/



# Segmentation/labeling datasets

- Segmentation/labeling datasets links:
  - Shape COSEG dataset [Wang et al. 2012]
    http://irc.cs.sdu.edu.cn/~yunhai/public_html/ssl/ssl.htm



- 1090 watertight meshes, obtained using active segmentation
- 2-5 parts / mesh

# Segmentation/labeling datasets

- Segmentation/labeling datasets links:
  - Labeled ShapeNet subset [Yi et al. 2016]
    http://web.stanford.edu/~ericyi/project_page/part_annotation/index.html


~30,000 shapes, ~90,000 parts

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