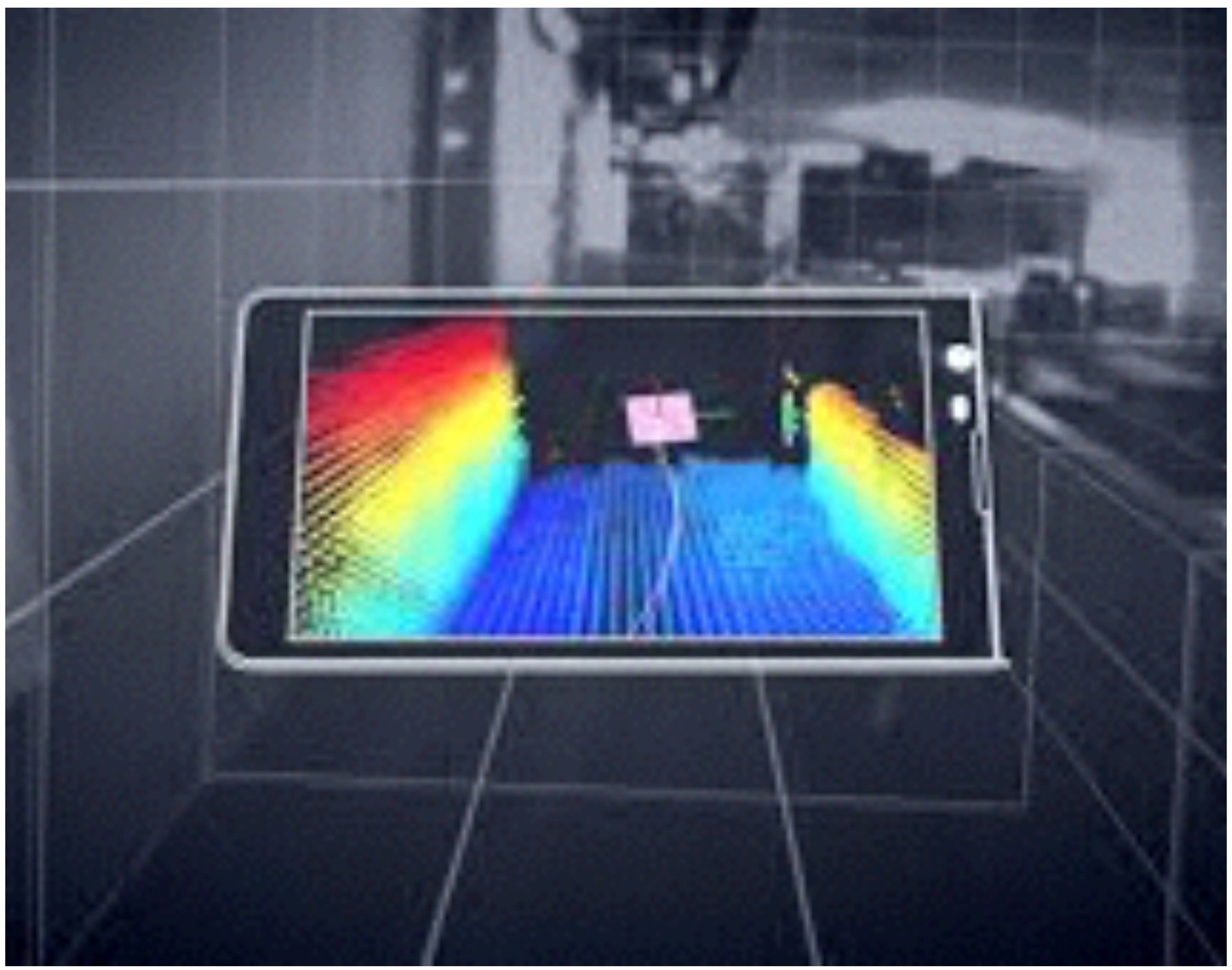
Part Structures in Large Collections of 3D Models

Vladimir Kim

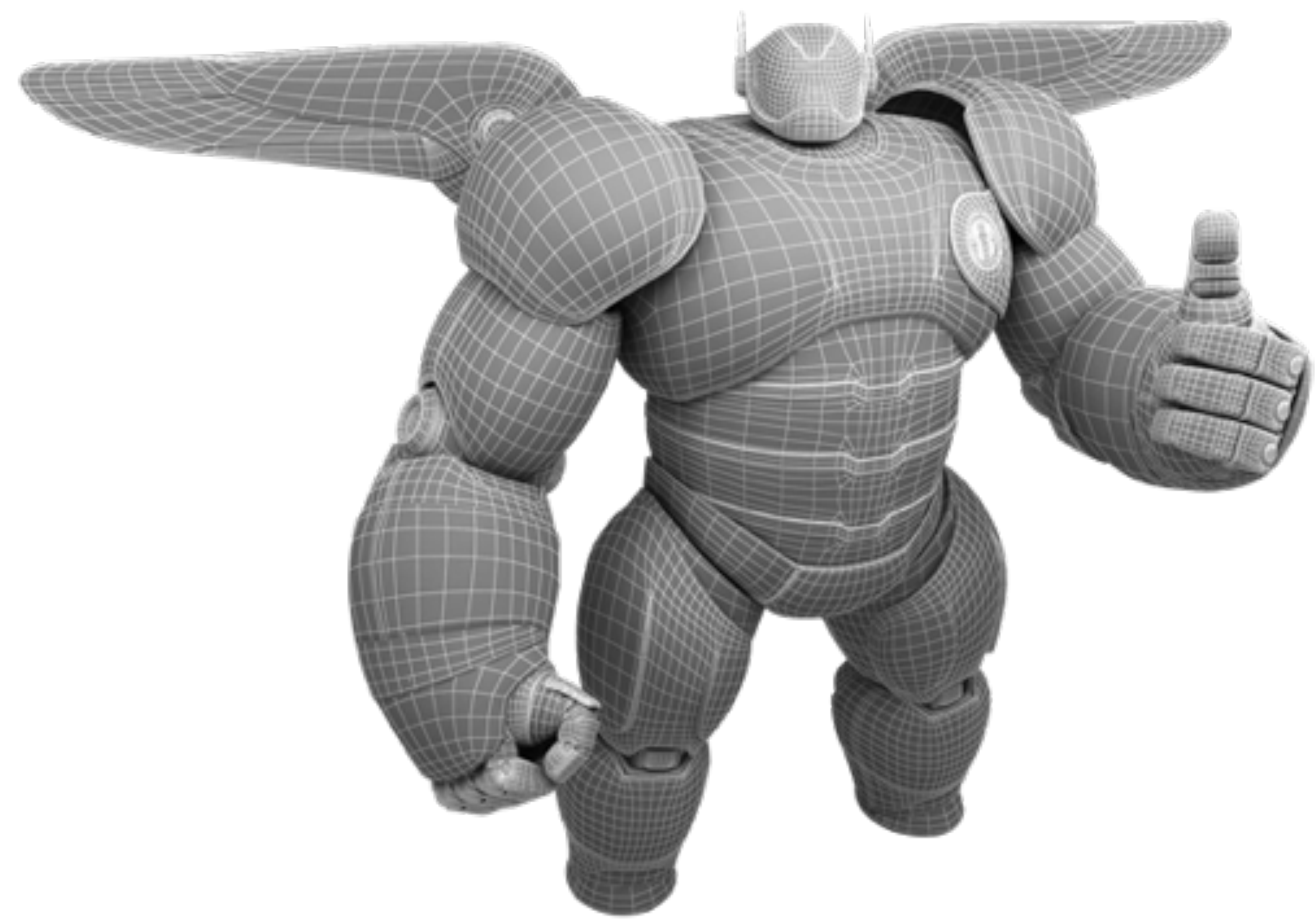
Adobe Research

Motivation

Explore, Analyze, and Create Geometric Data



Real



Virtual

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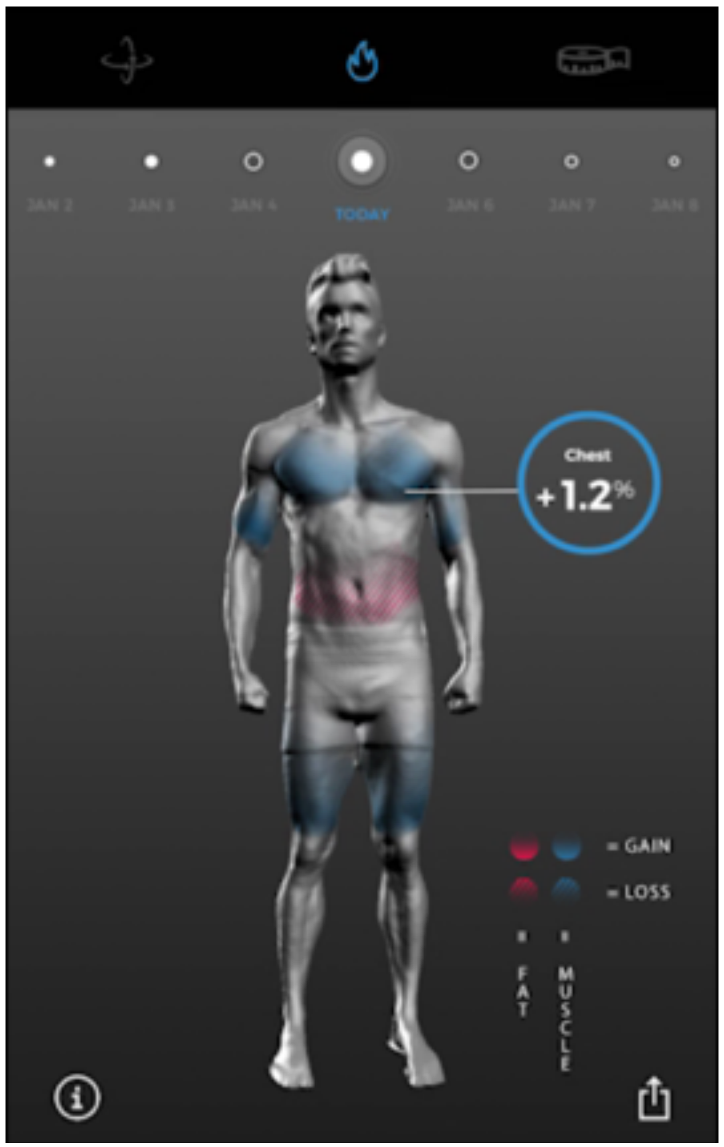

Personal data

(image from naked.fit)

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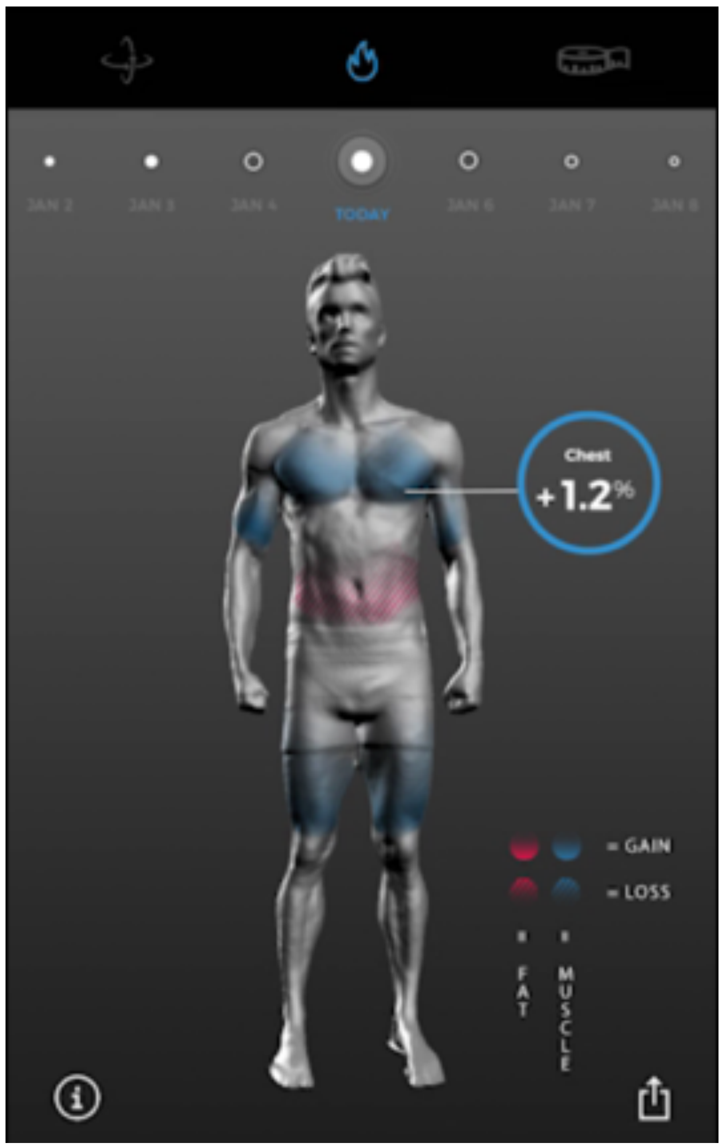

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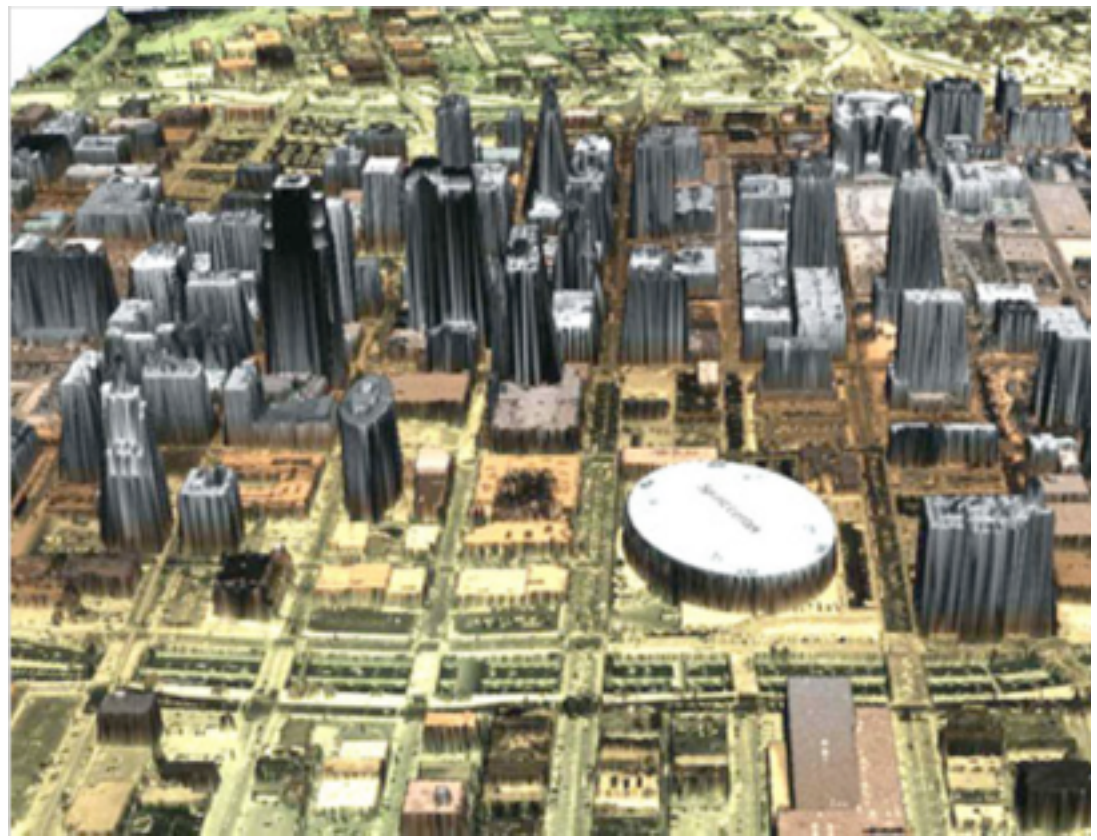

Scans of environments

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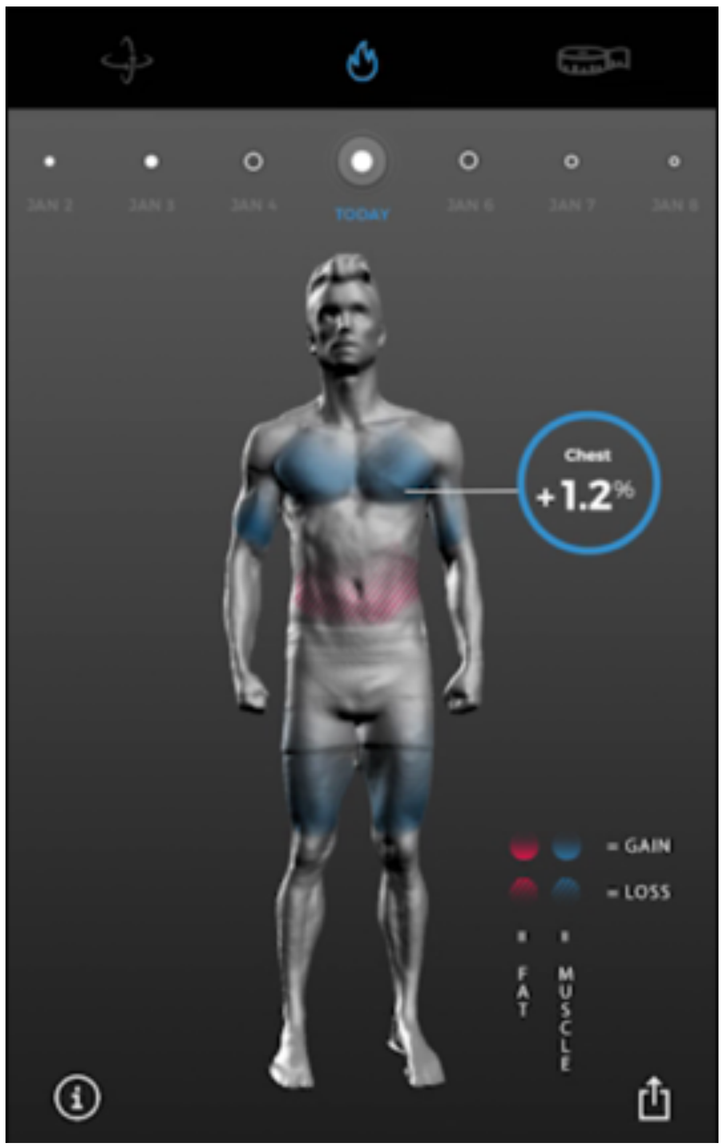

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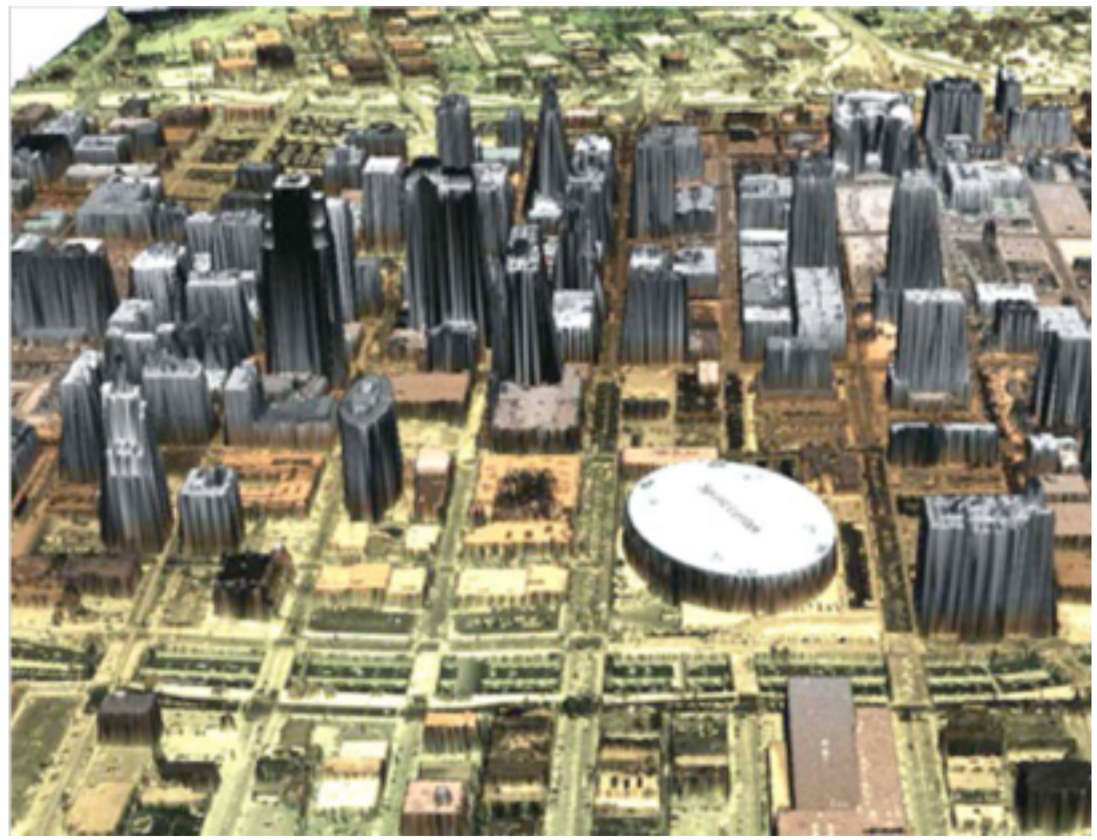

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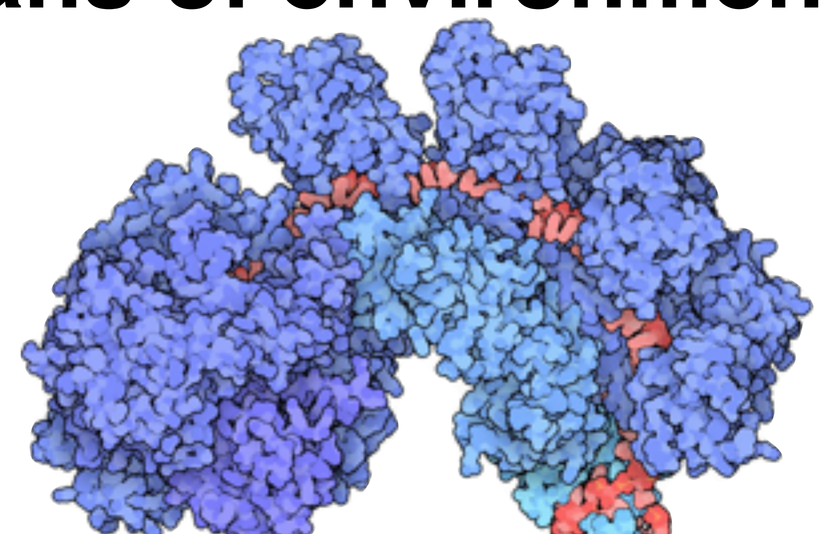
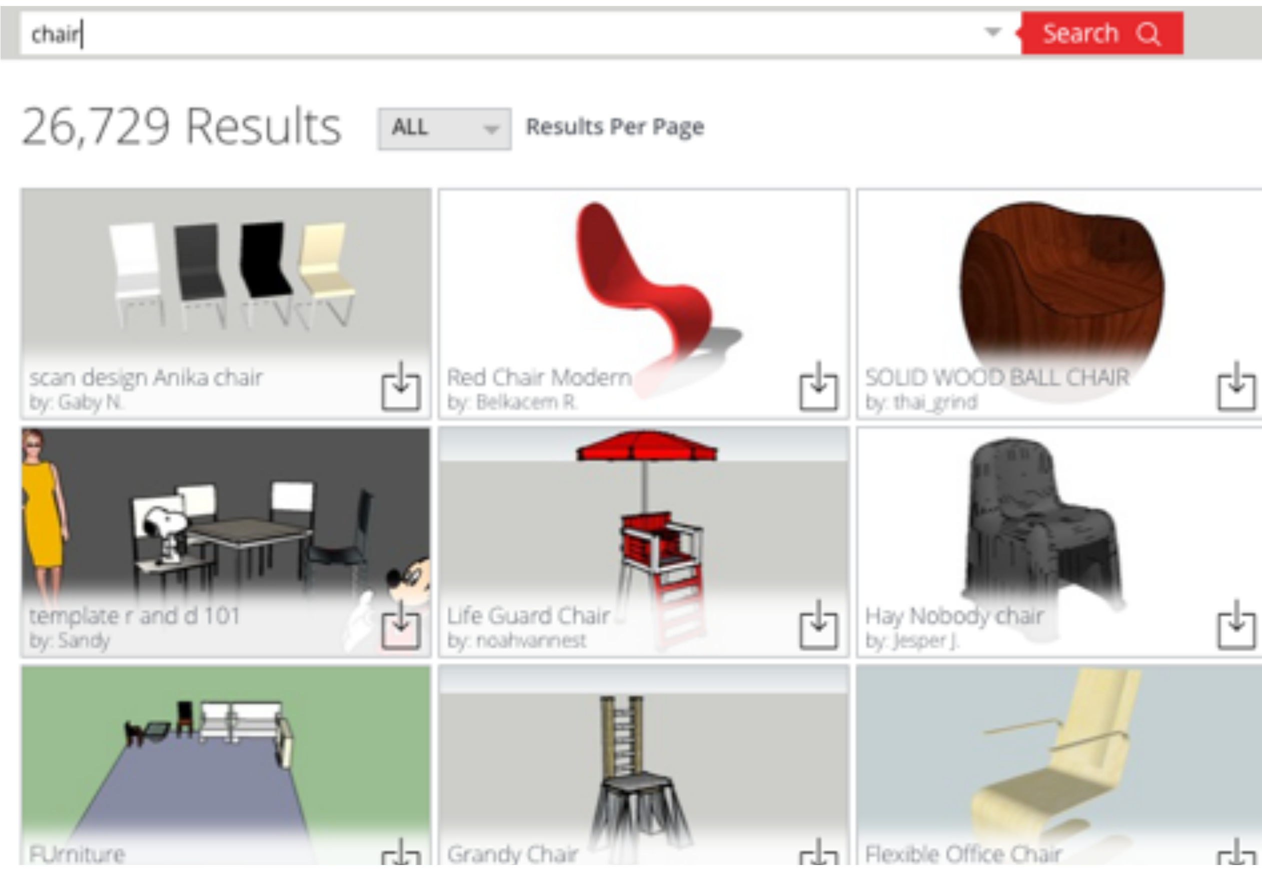


Scientific data

Medical Imaging

Motivation

Explore, Analyze, and Create Geometric Data



CG data

(image from 3dwarehouse.sketchup.com)

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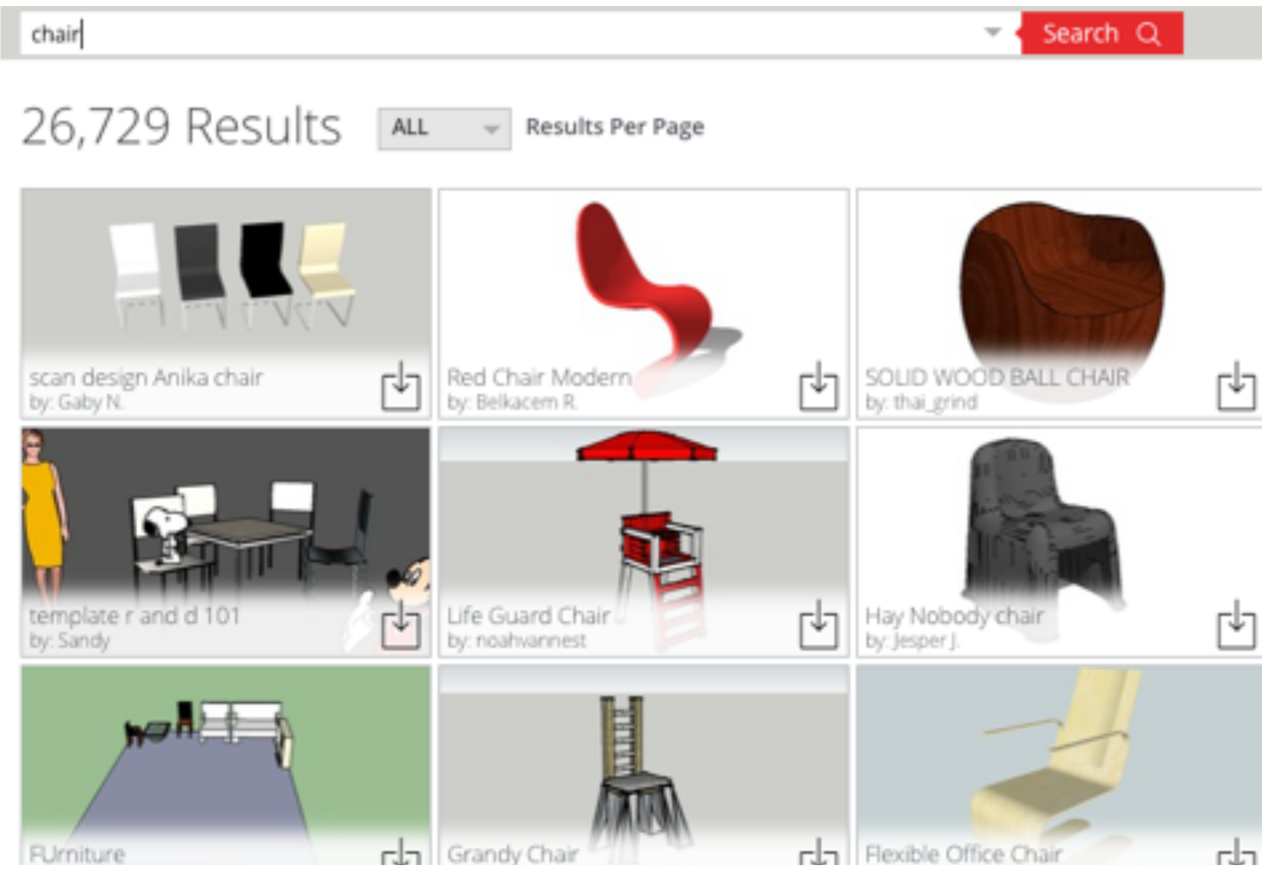

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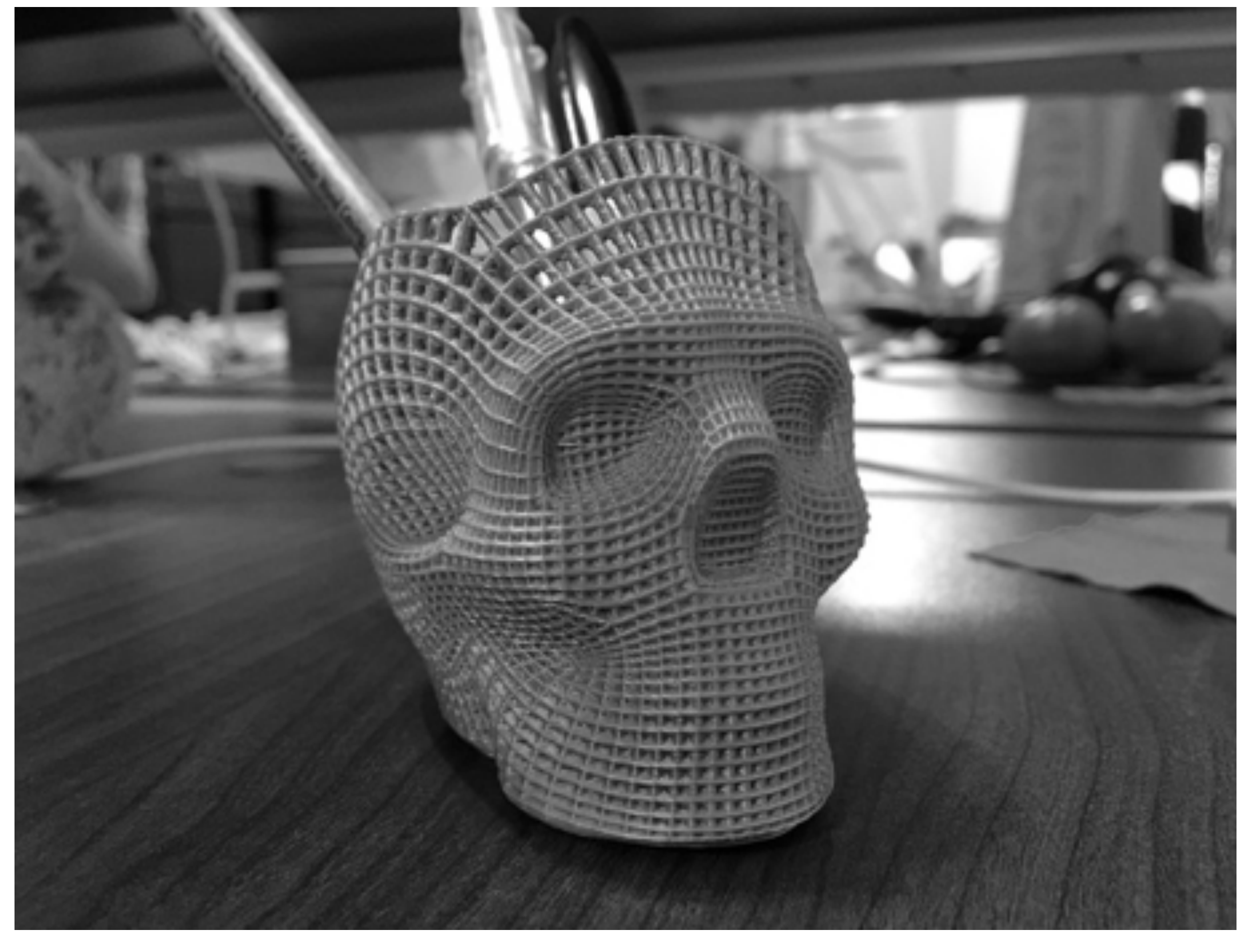

3D printing data
(image from thingiverse.com/)

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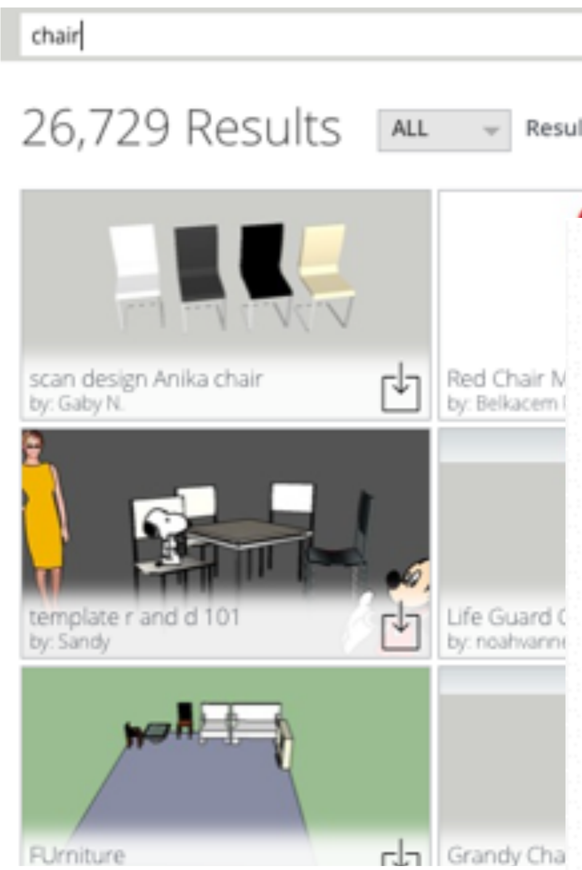

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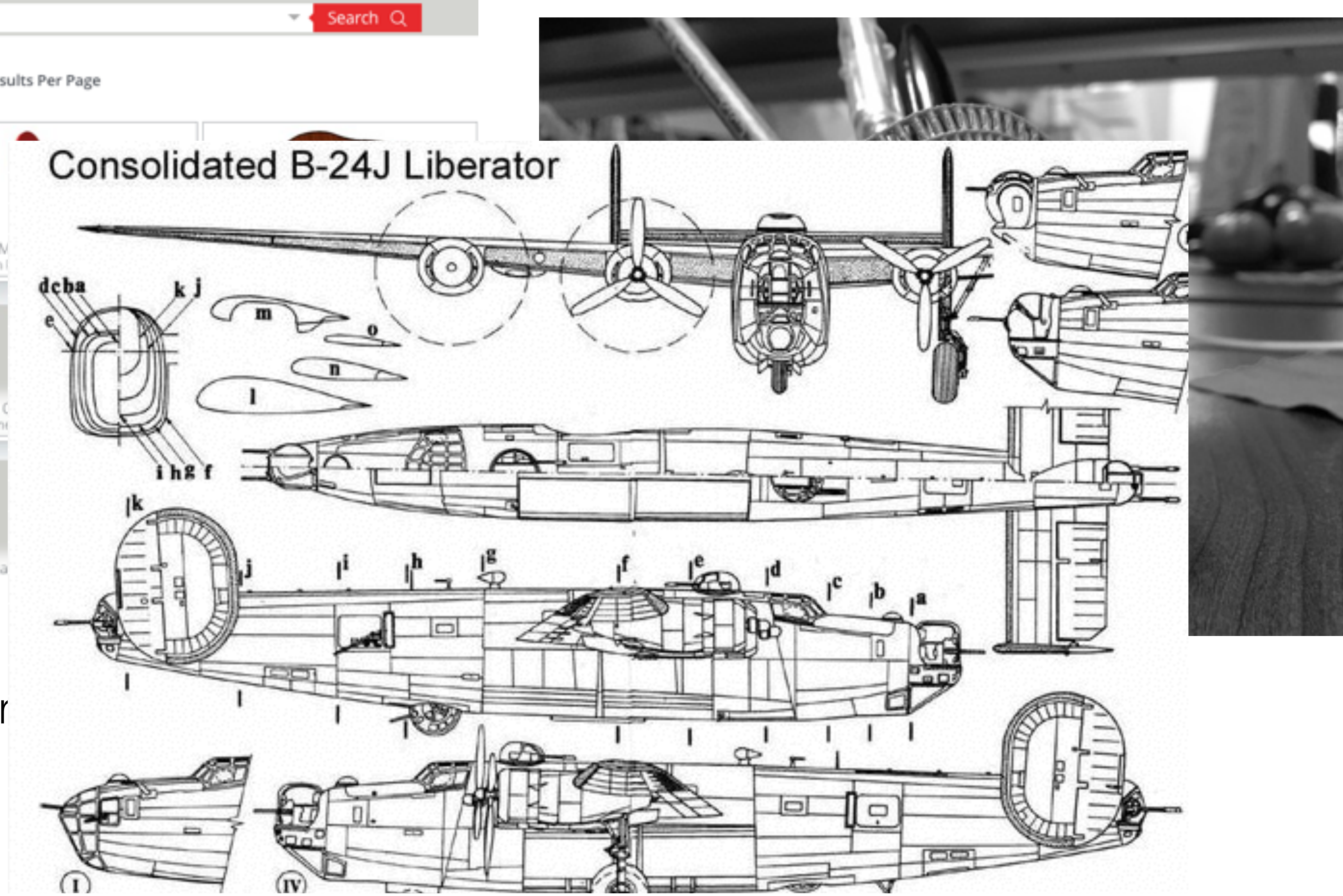
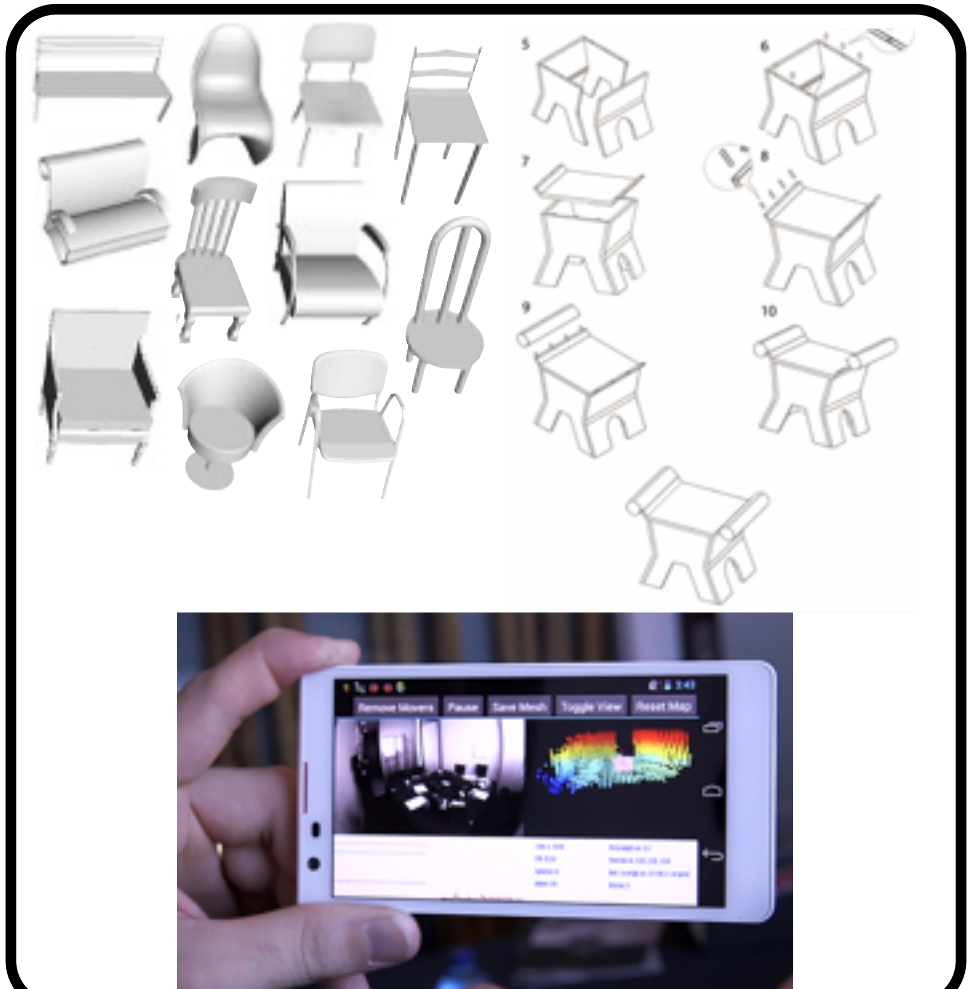


CAD models

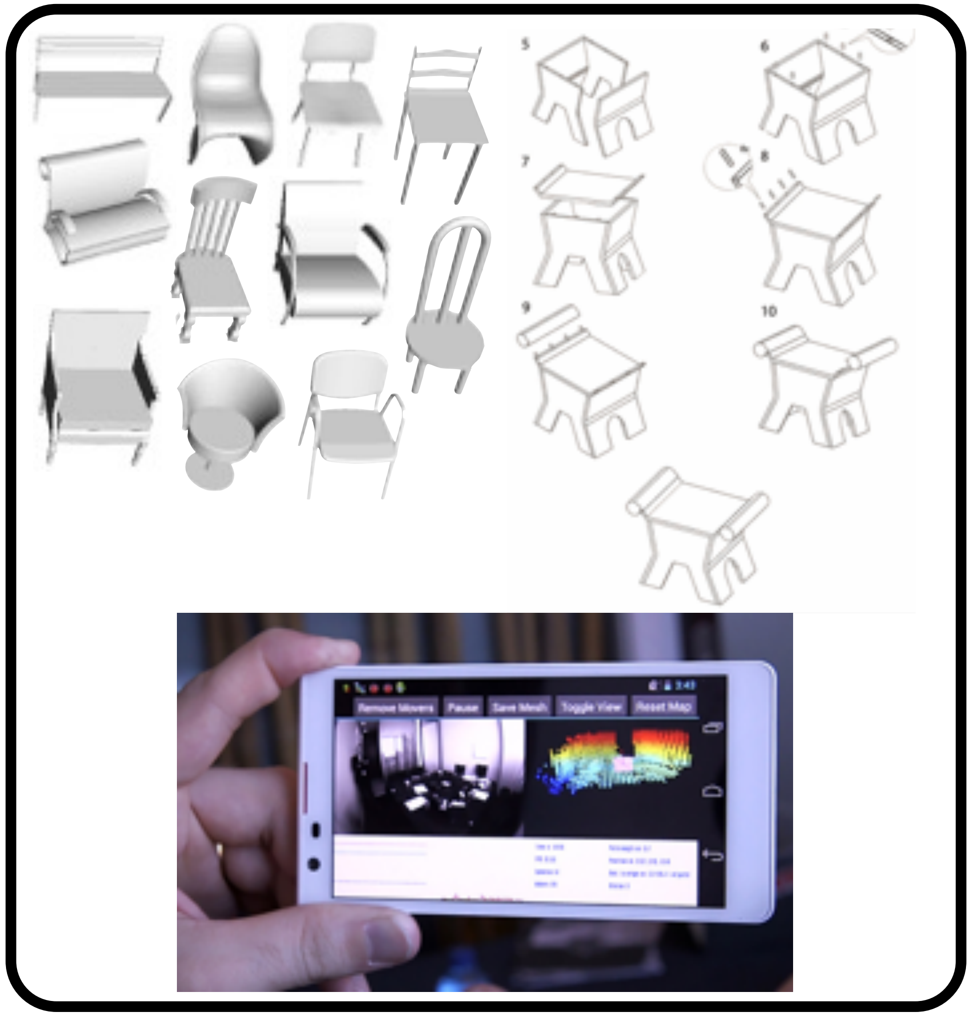
Goal



3D Data

→ **Structural Model** → **Applications**

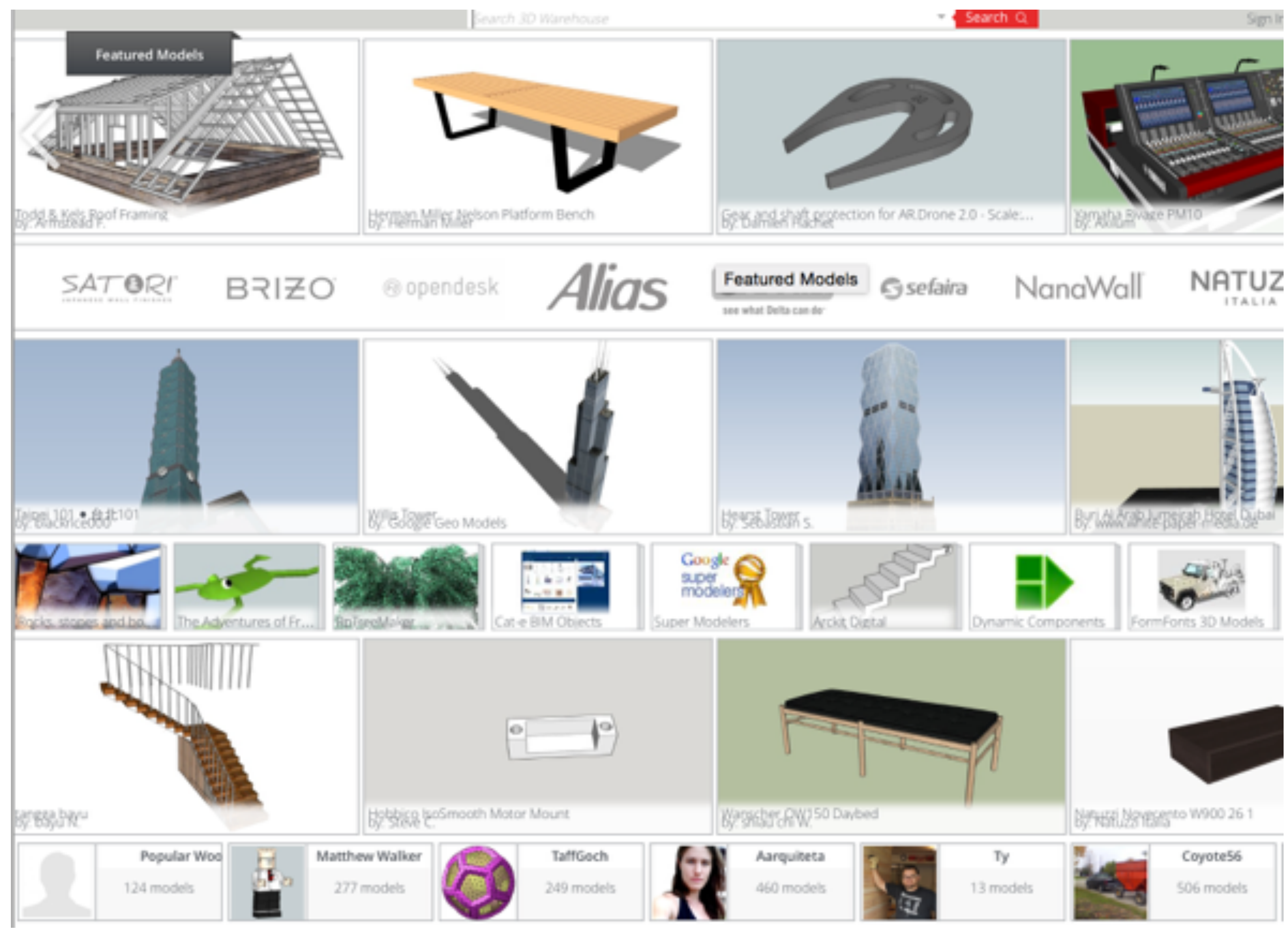
Goal



3D Data

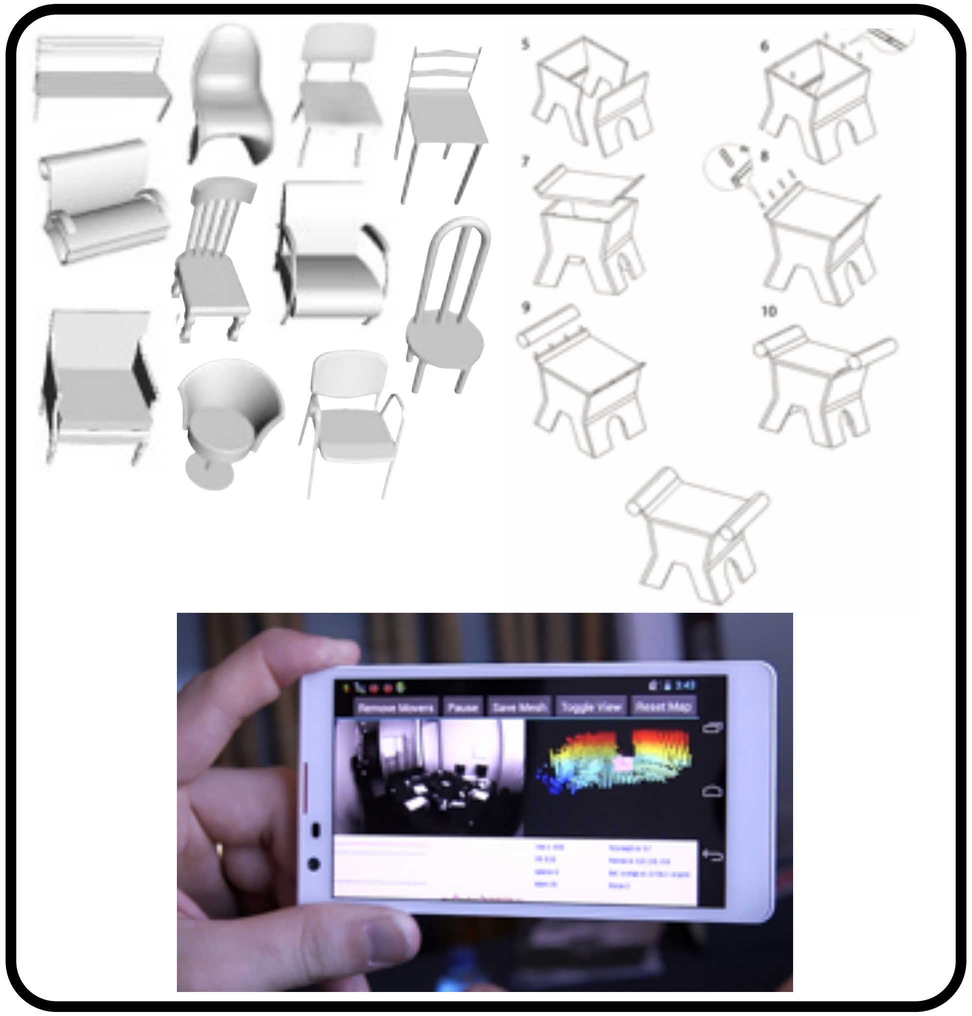
Structural Model

Explore



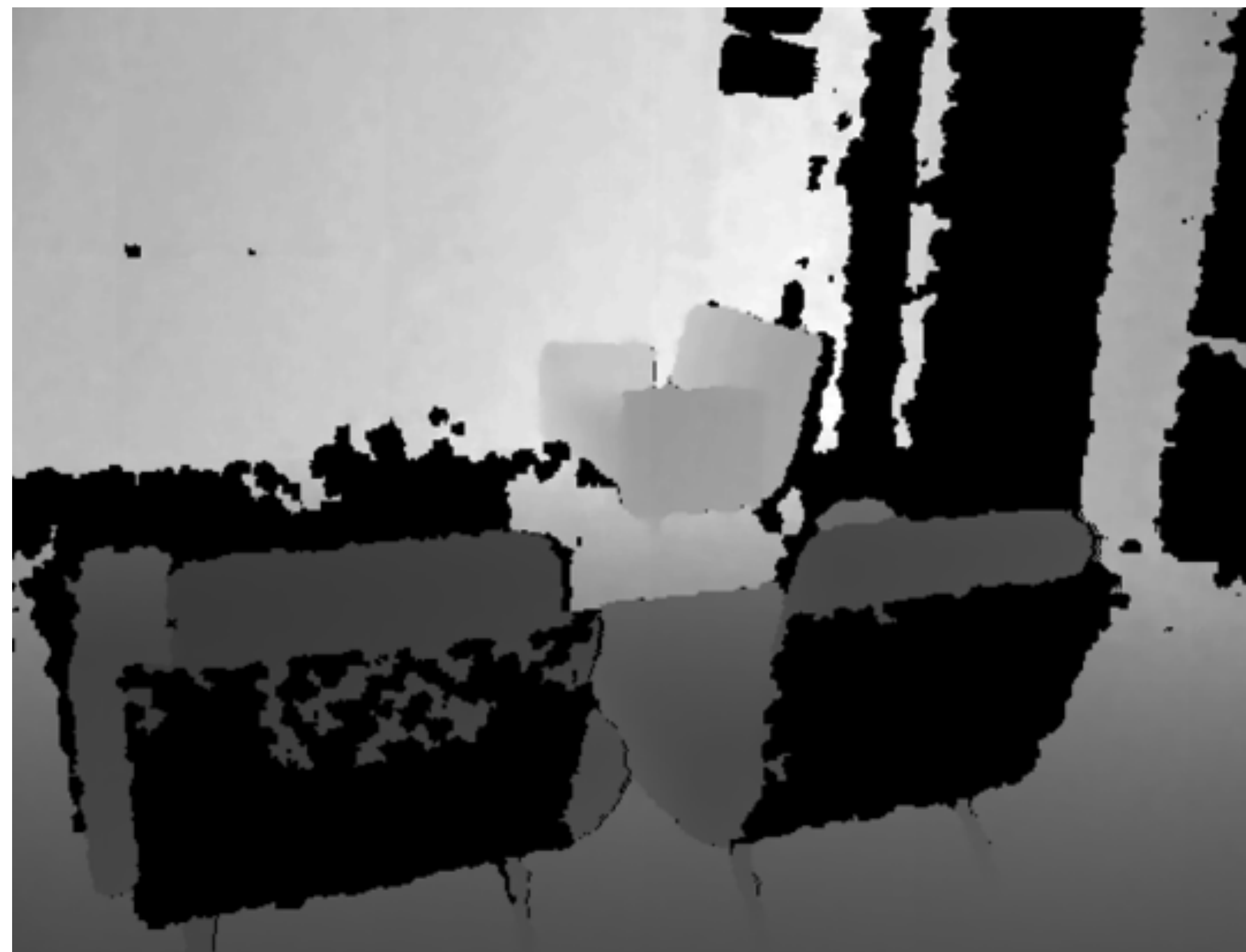
Organize and explore large collections of shapes

Goal



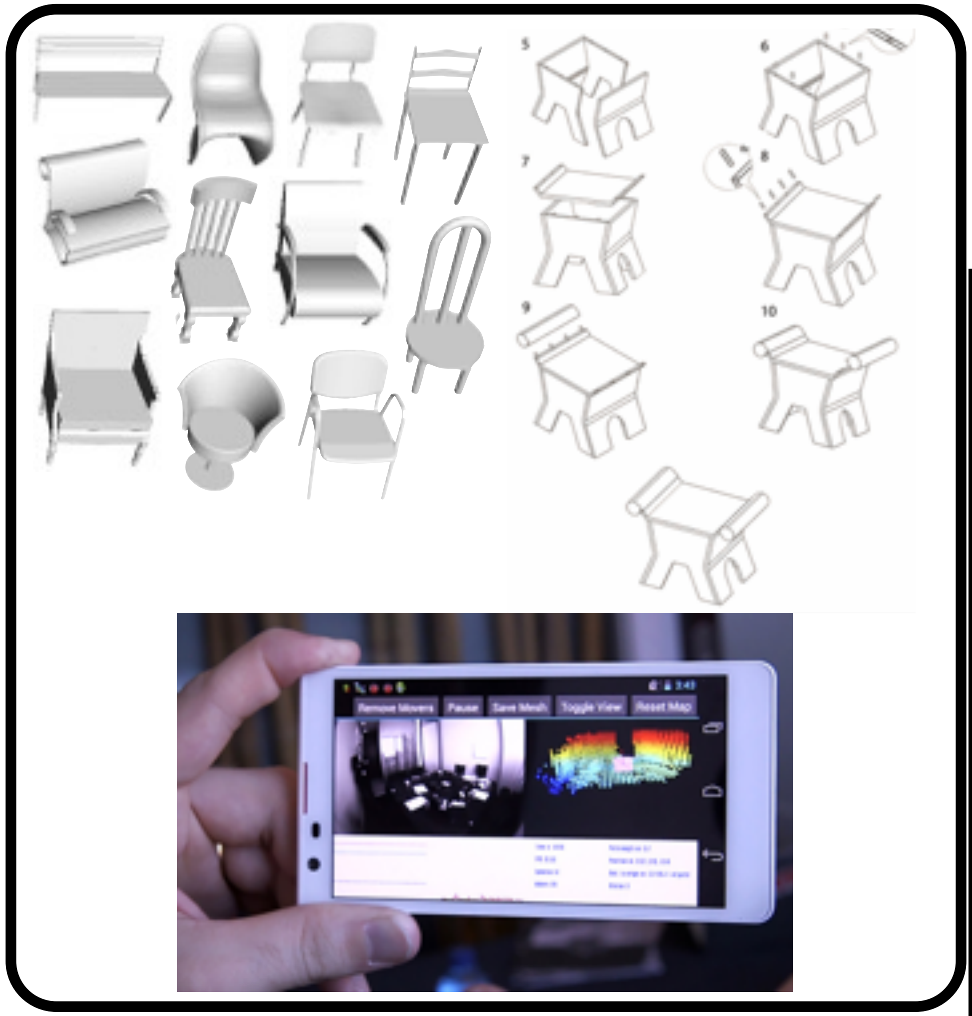
3D Data

→ **Structural Model** → **Analyze**



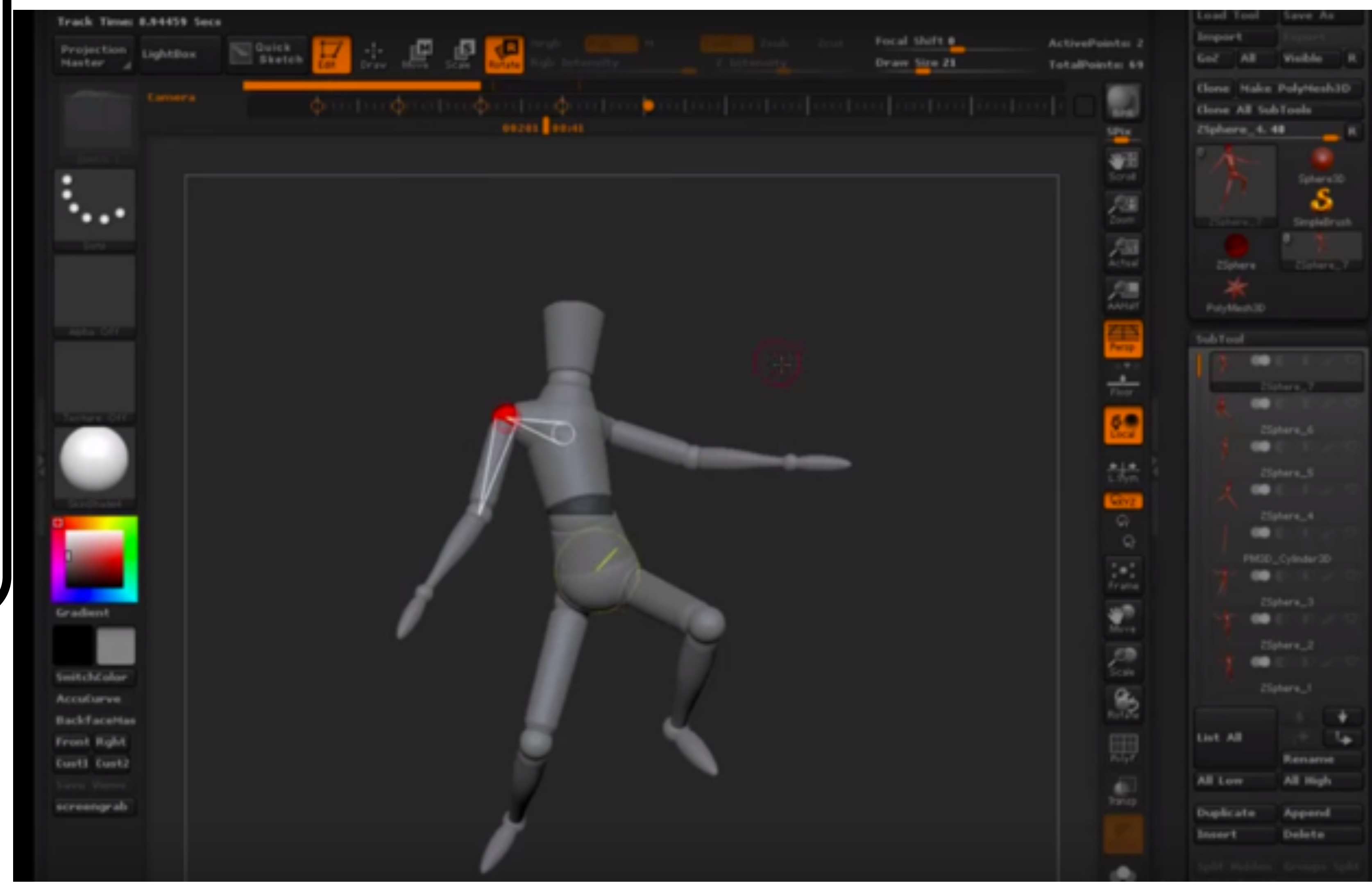
Understand and label novel geometric data

Goal



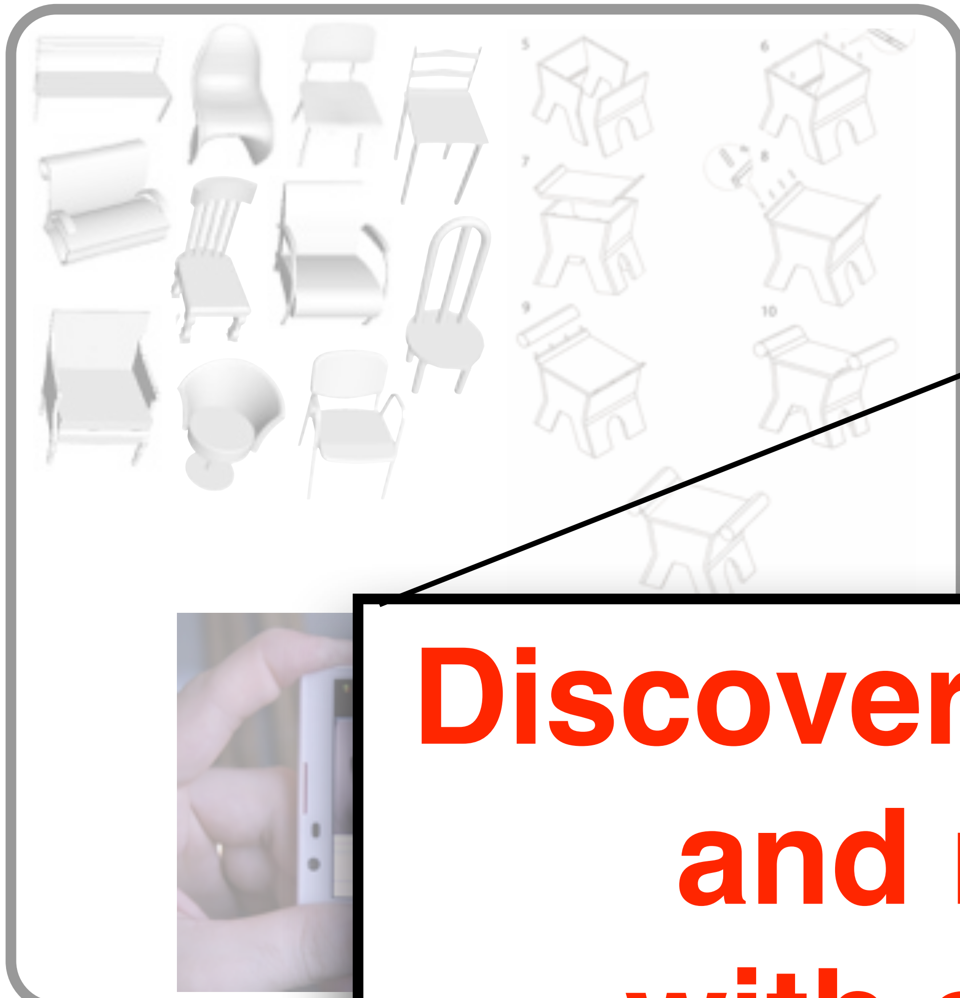
3D Data

→ **Structural Model** → **Create**



Make 3D modeling more accessible to non-experts

Goal



Structural Model

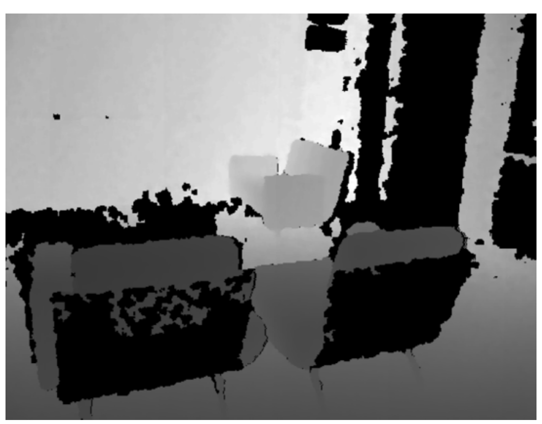
Create

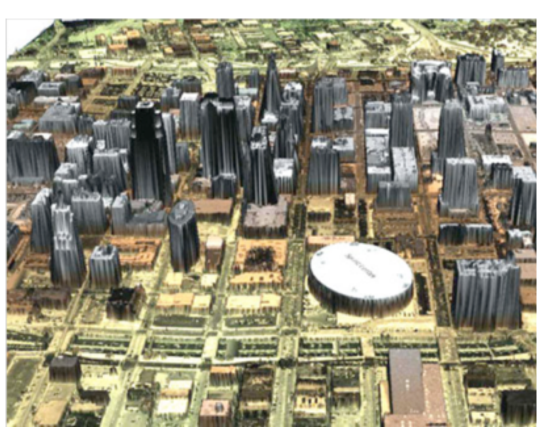
Discover repeating patterns and represent them with a concise model

Make 3D modeling more accessible to non-experts

Challenges

Discover common structure





Diversity

TurboSquid

3D Warehouse

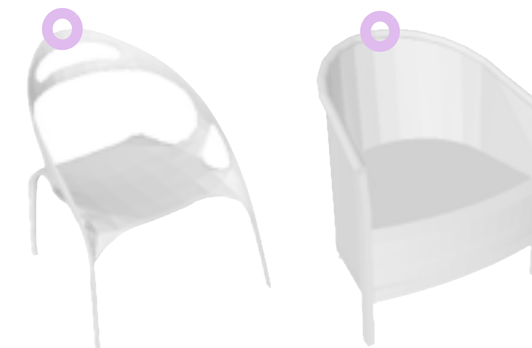
shapeways

Thingiverse

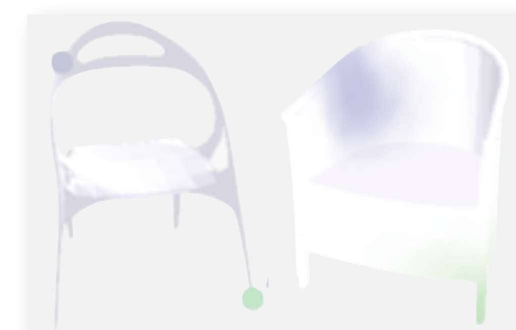
ShapeNet

Project Tango

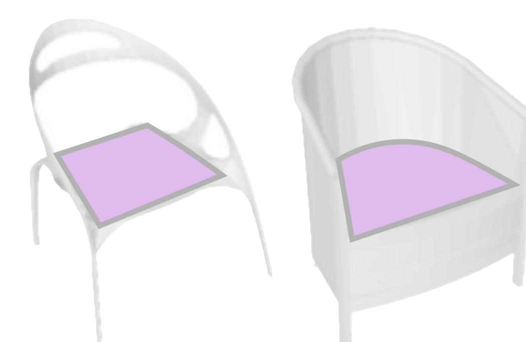
Scale



Point-to-point



Region-to-region

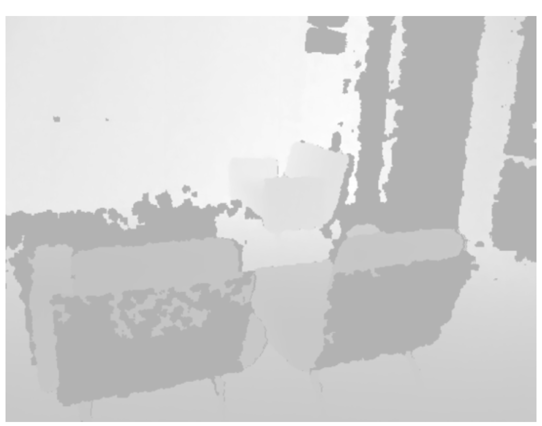


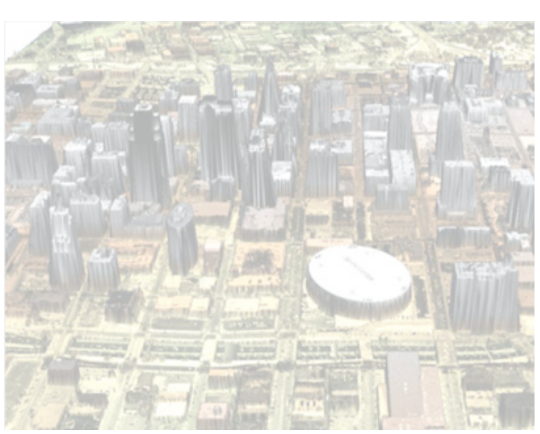
Part-to-part

Ambiguity

Challenges

Discover common structure





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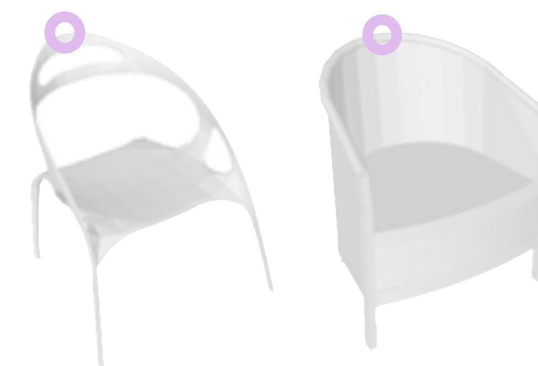
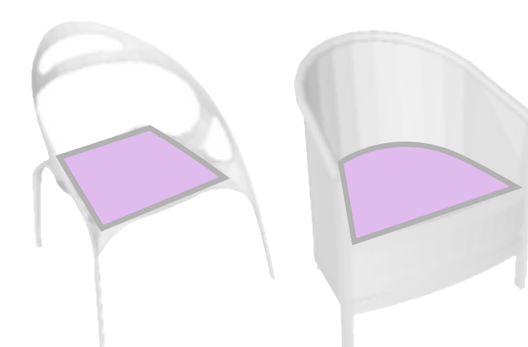


Point-to-point

Region-to-region



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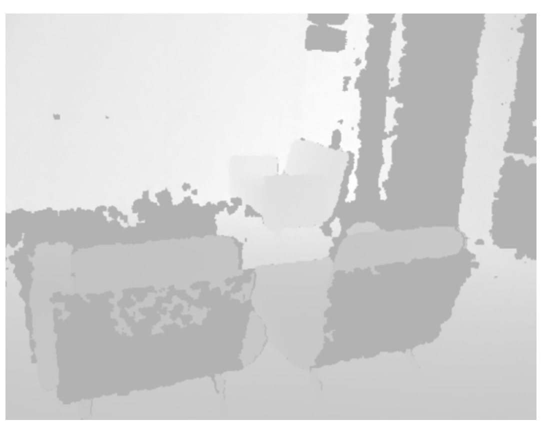

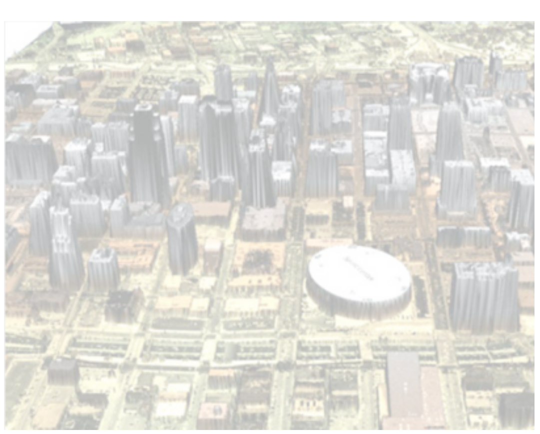

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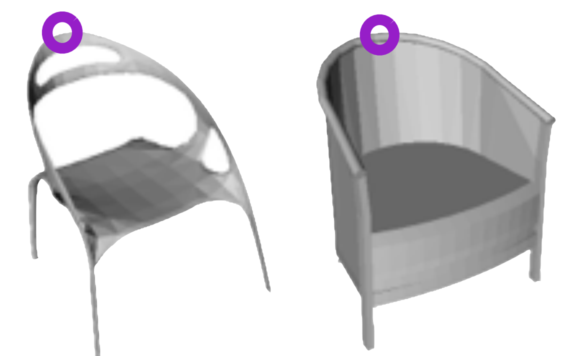
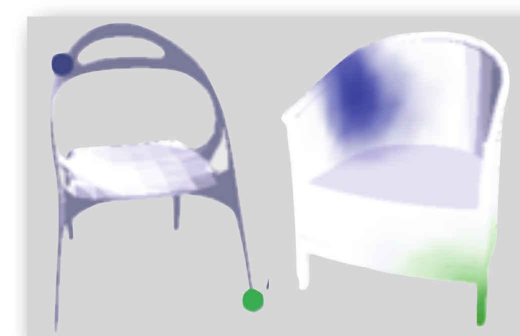


Point-to-point



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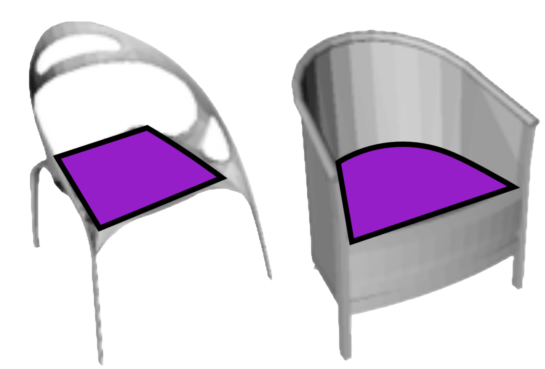
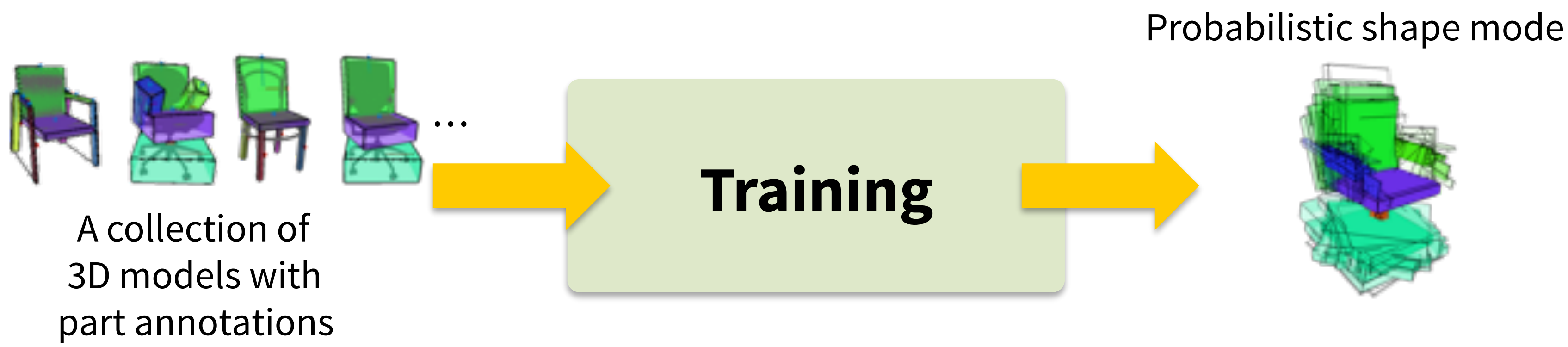


Part-to-part

Ambiguity

Part-based Template

Template is learned from segmented objects



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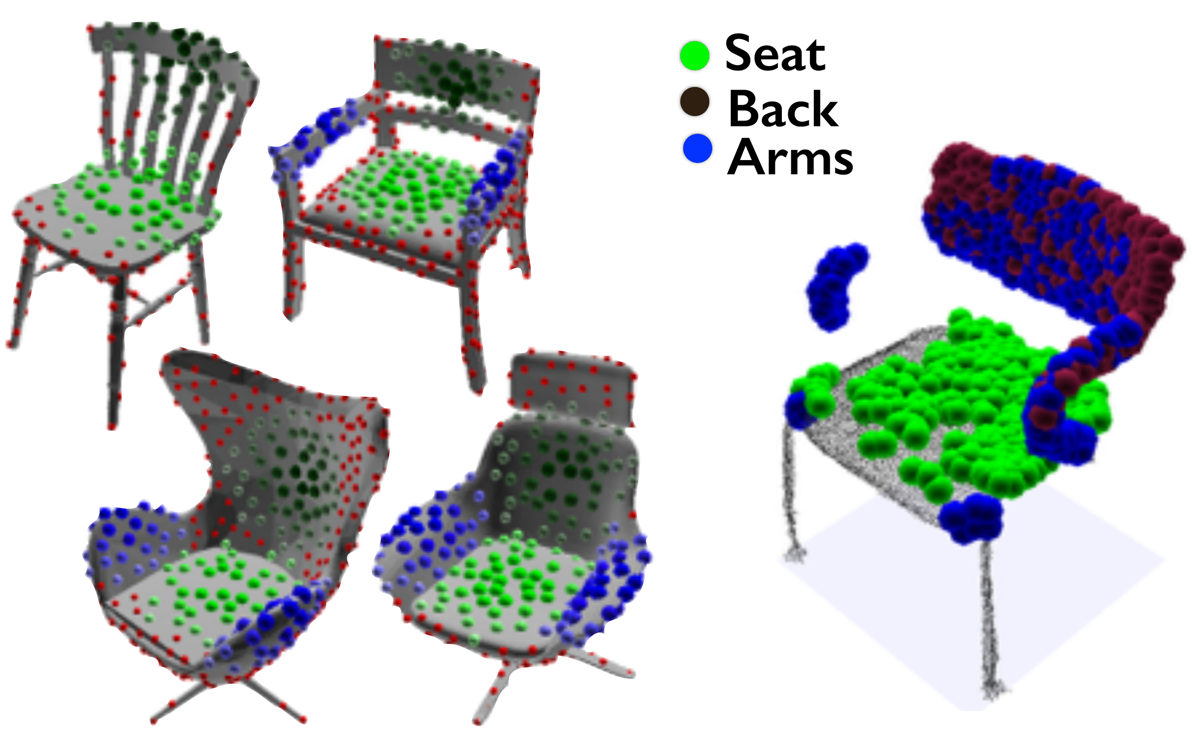
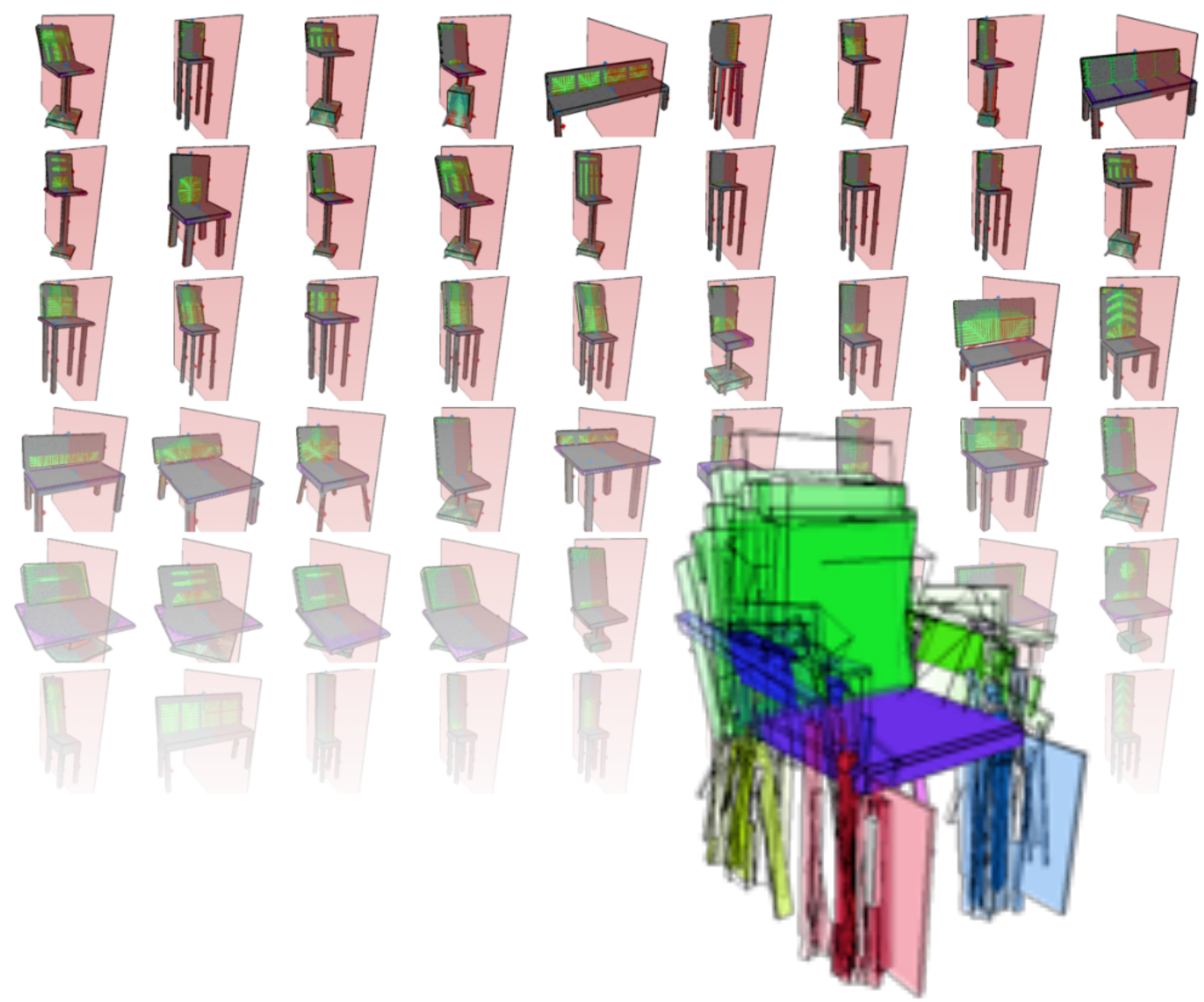


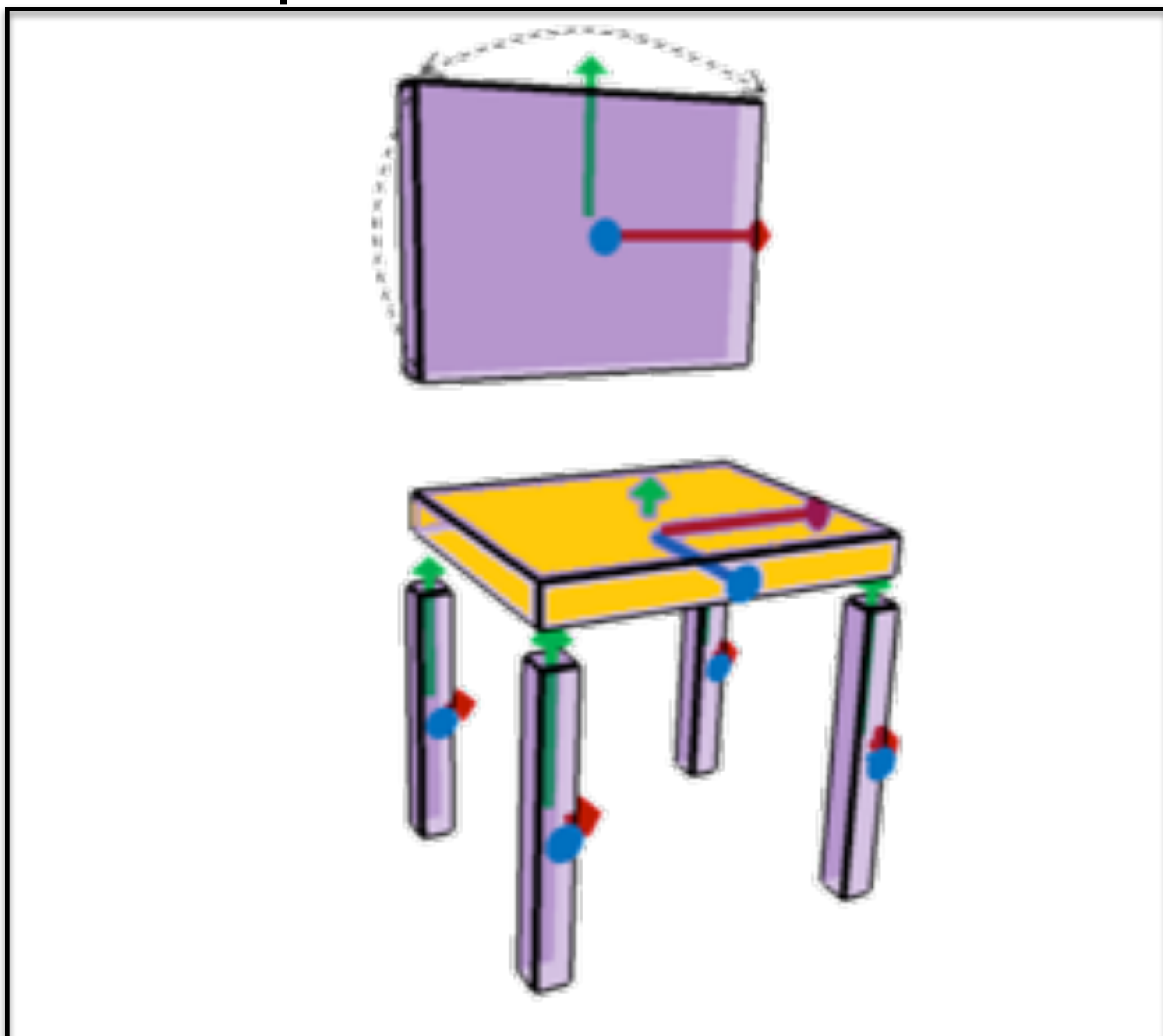


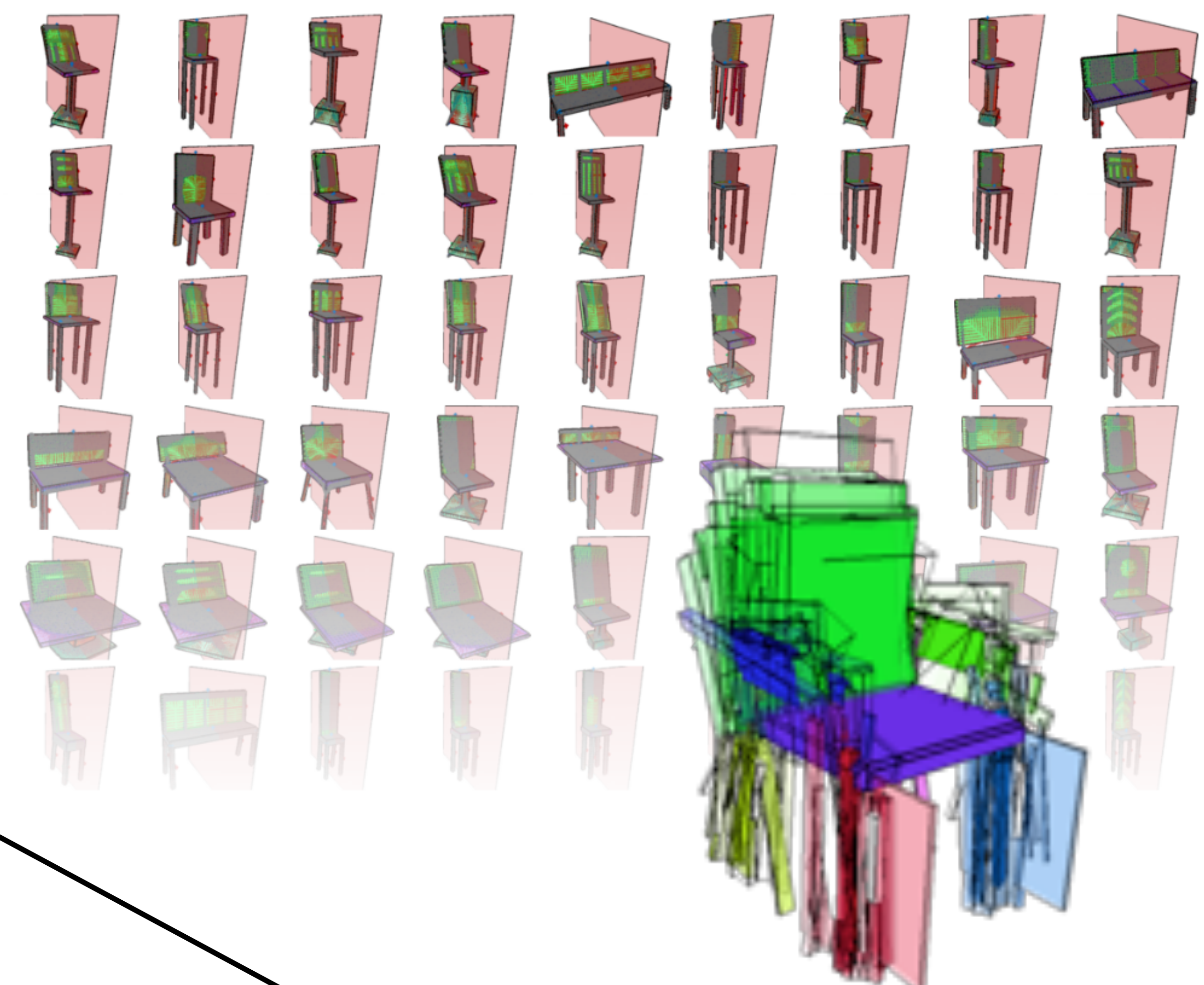
Per-point classifiers

Pairwise part relations

Part-based Template

Template is learned from segmented objects





Pairwise part relations

Each part is a local coordinate system
Represent all other parts in this coordinate system
Probabilistic distribution (e.g., Gaussian)

Structure Inference

Fitting template for structure inference

➡ **Input**

- Initialization
- Part labels and orientations
- Point segmentation
- Pose optimization
- Additional part candidates

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$$E = E_{\mathrm{pnt}} + E_{\mathrm{dist}} + E_{\mathrm{part}}$$

Classifiers	Template distance	Part Relations

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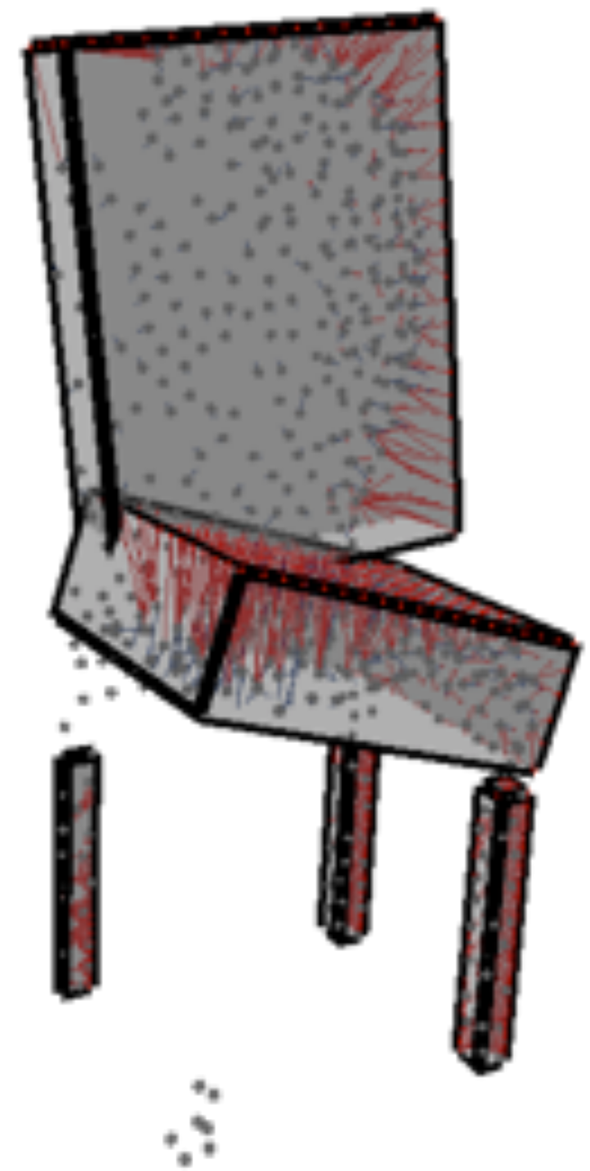

Opt: Clustering

$$E = \boxed{E_{\text{pnt}}} + E_{\text{dist}} + E_{\text{part}}$$

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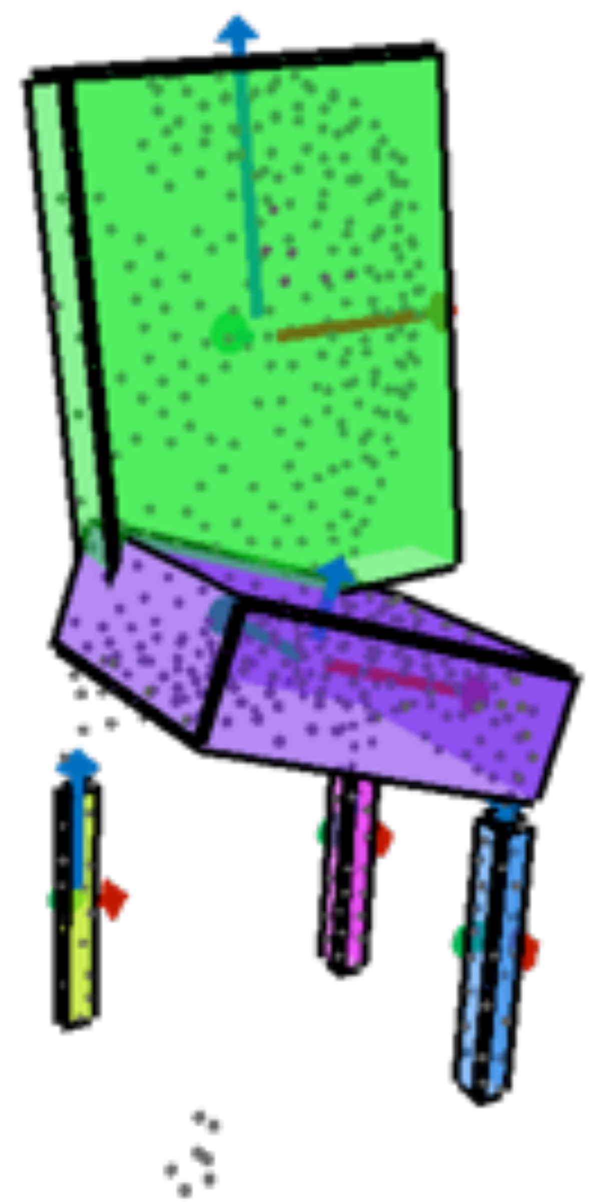

Opt: CRF (at segment level)

$$E = \boxed{E_{\text{pnt}} + E_{\text{dist}} + E_{\text{part}}}$$

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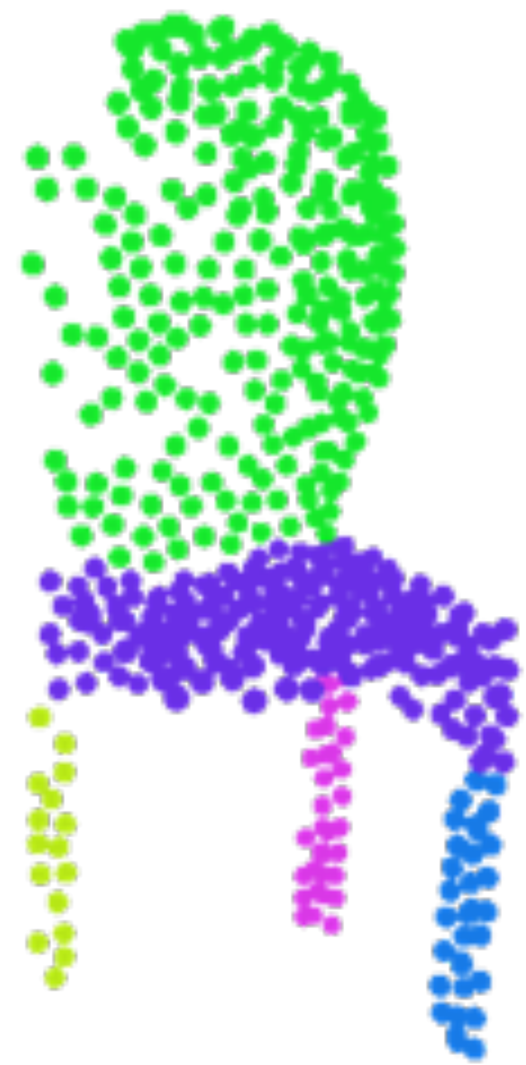

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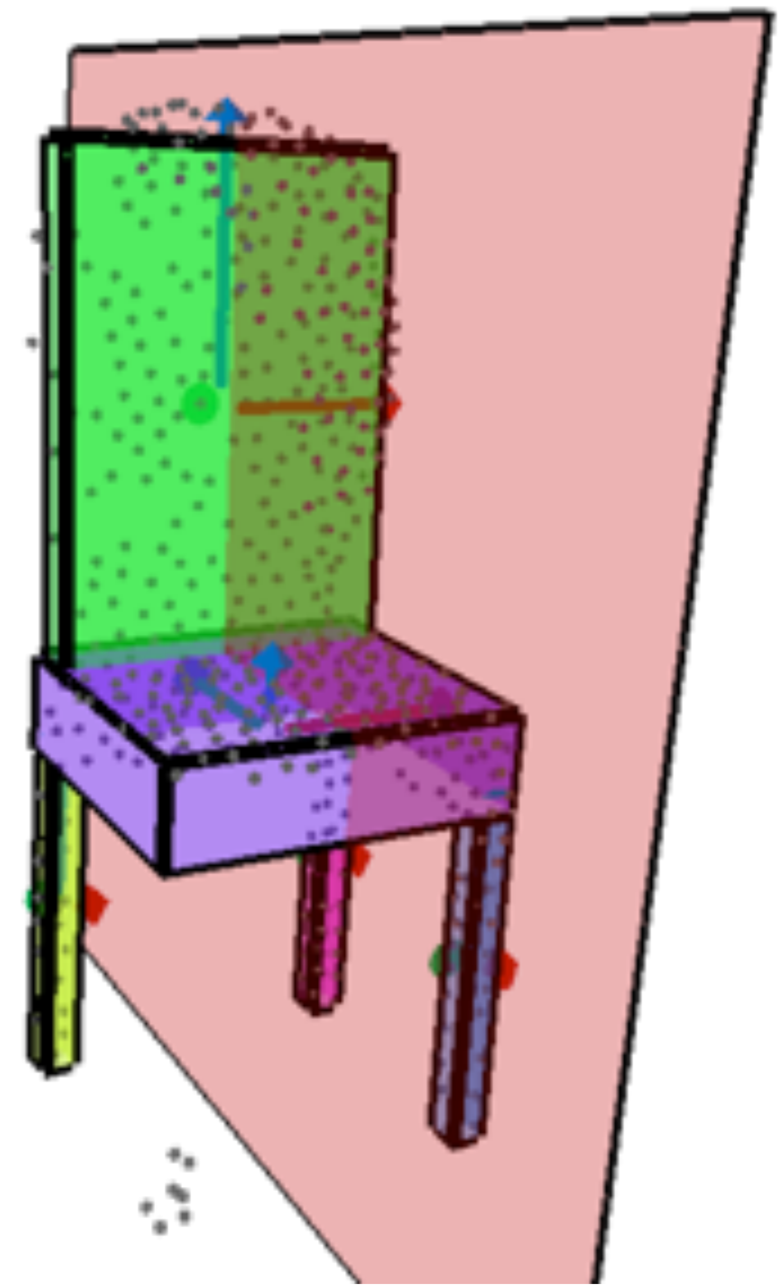

Opt: Gradient Descent

$$E = E_{\mathrm{pnt}} + \boxed{E_{\mathrm{dist}} + E_{\mathrm{part}}}$$

Structure Inference

Fitting template for structure inference

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➡ **Additional part candidates**

Opt: greedy sampling

$$E = E_{\text{pnt}} + E_{\text{dist}} + \boxed{E_{\text{part}}}$$

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Fitting template for structure inference

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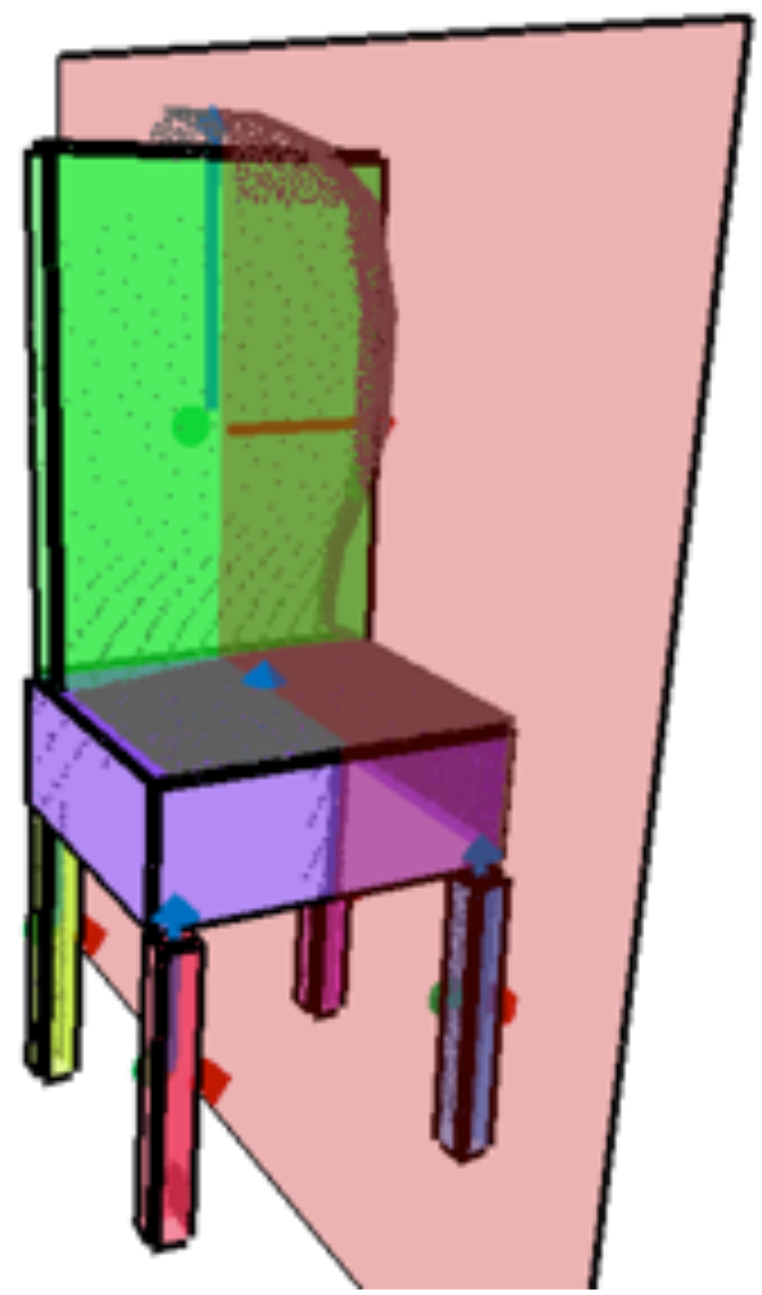
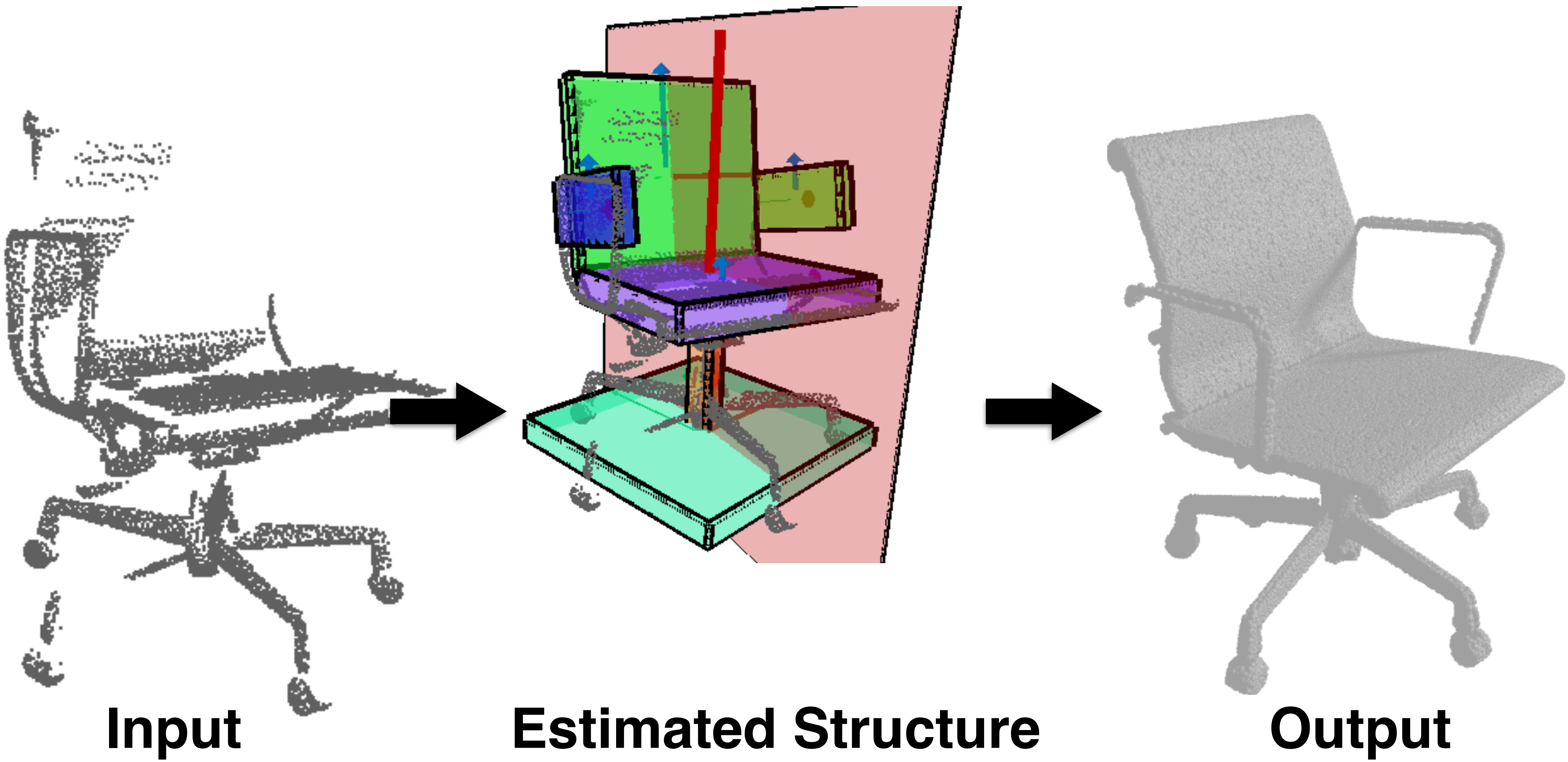
- Additional part candidates

Final Result:



Shape Completion



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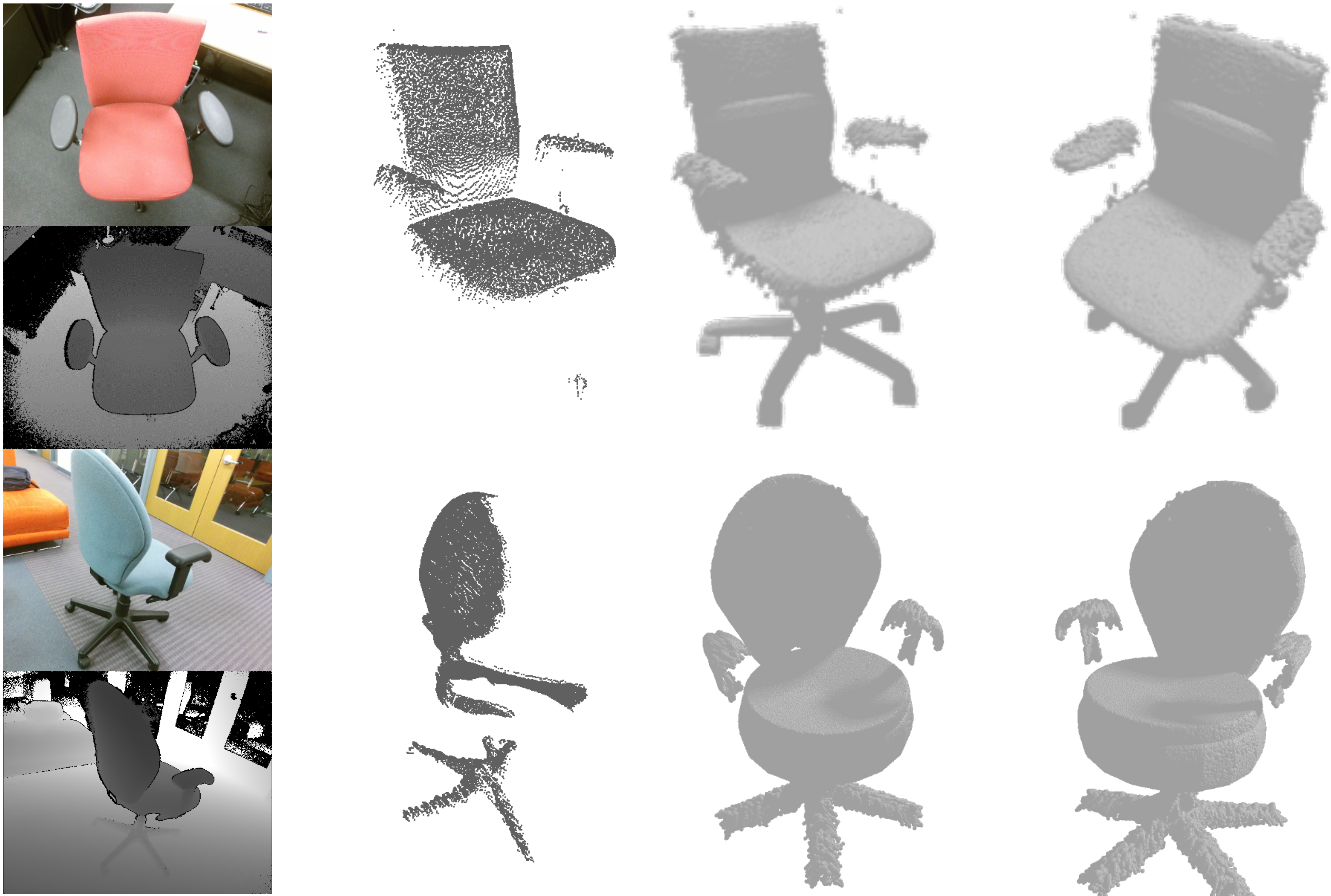
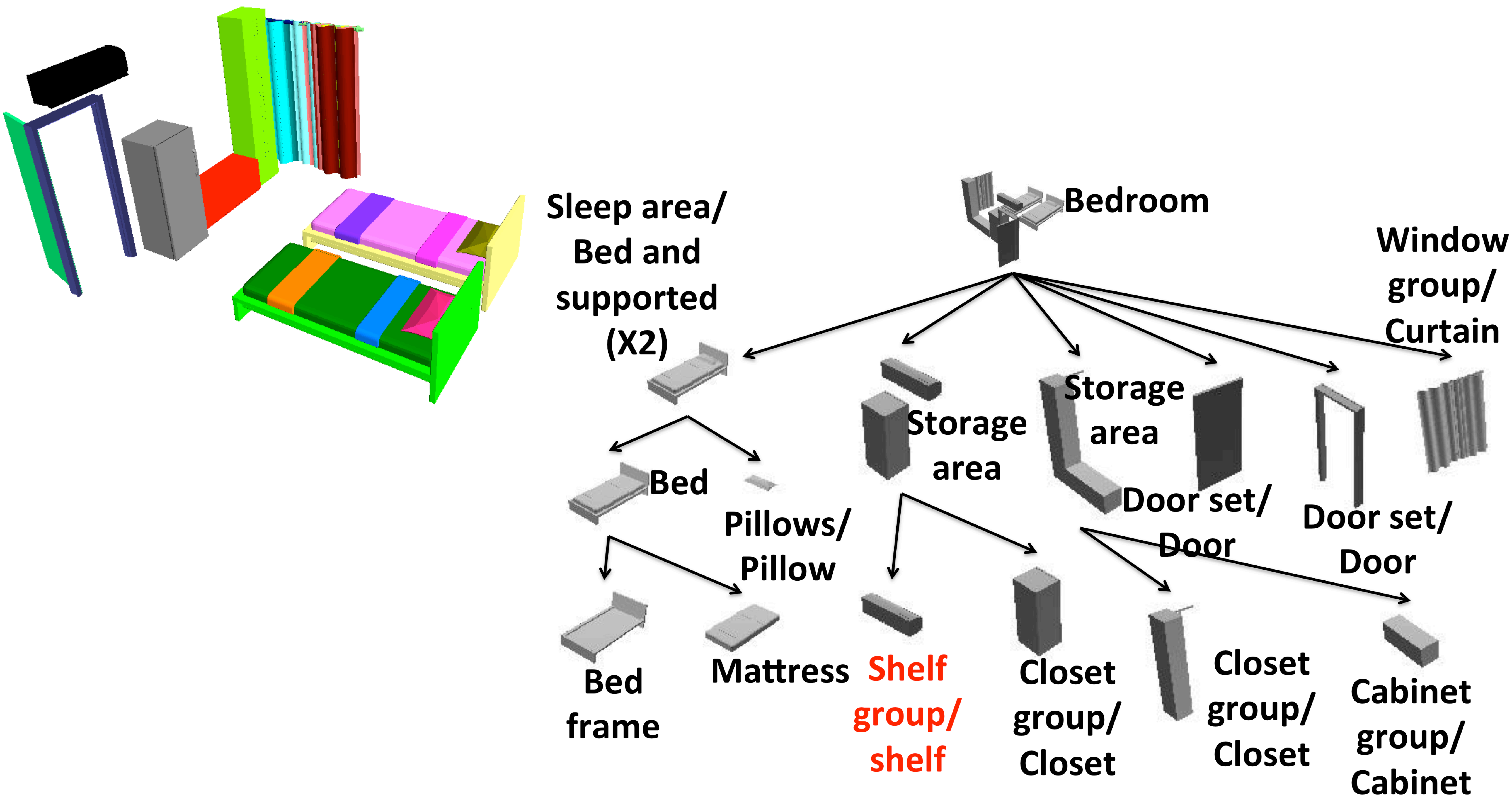


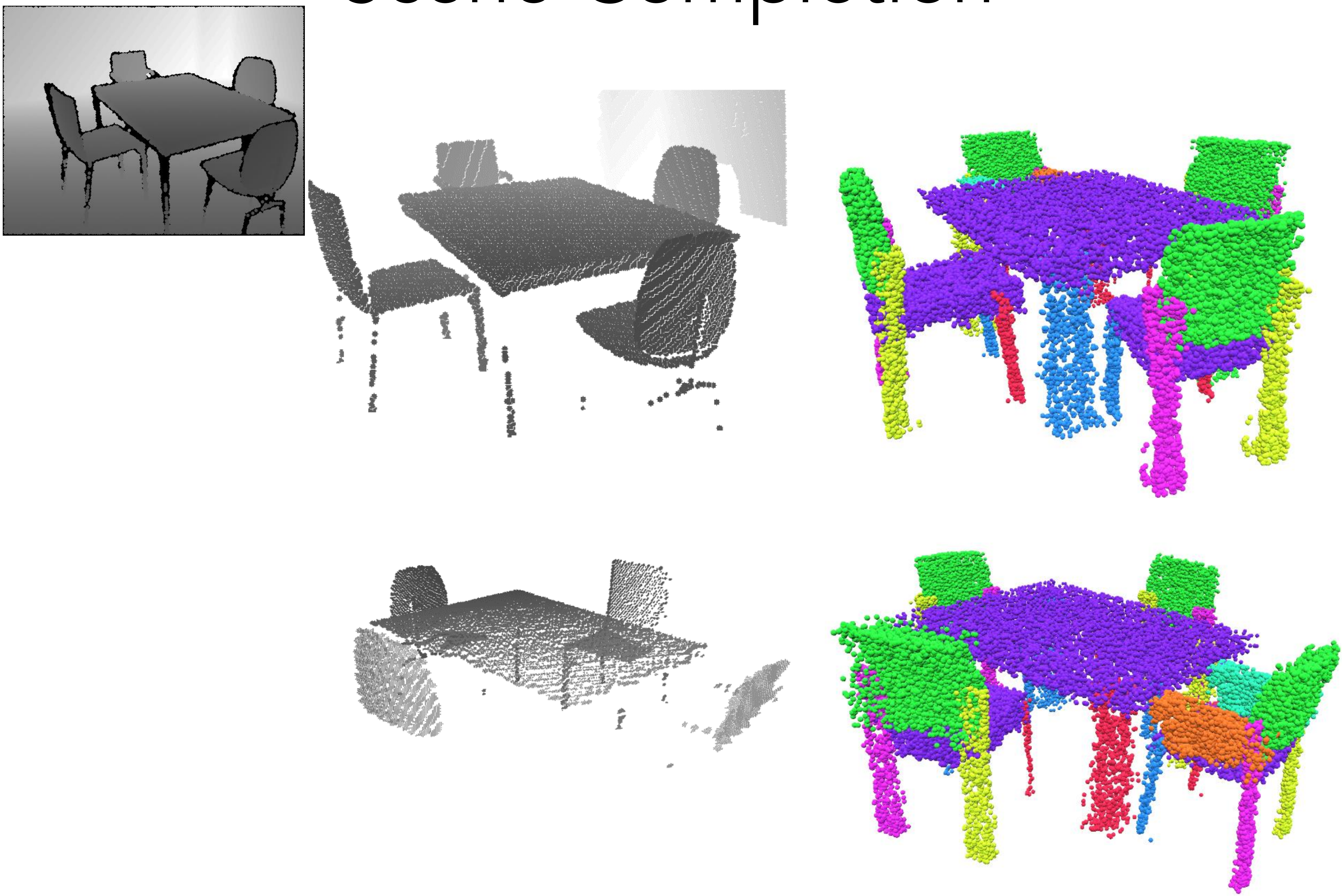
Shape Completion

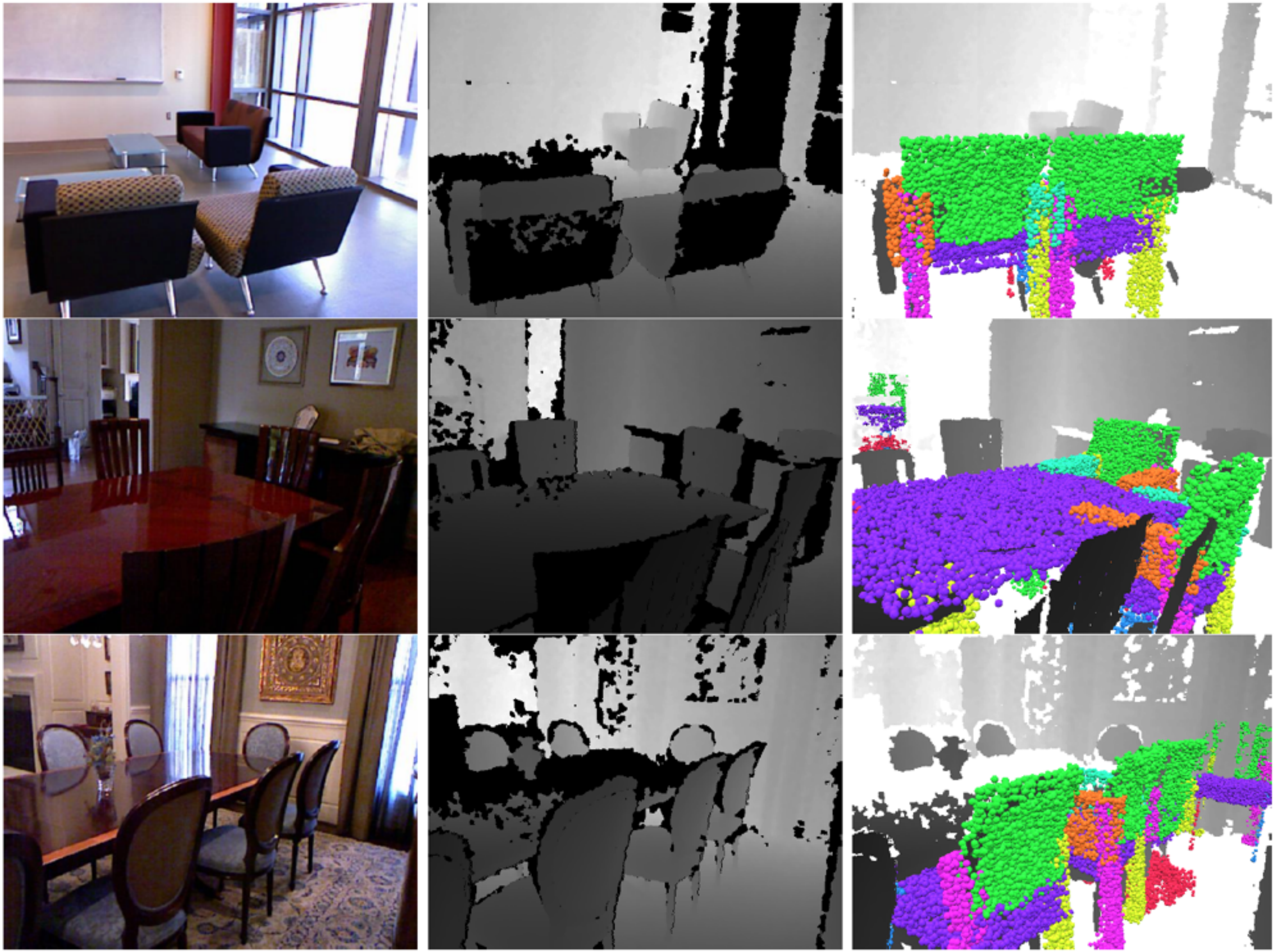
Hierarchical Templates

Use probabilistic grammars for hierarchies

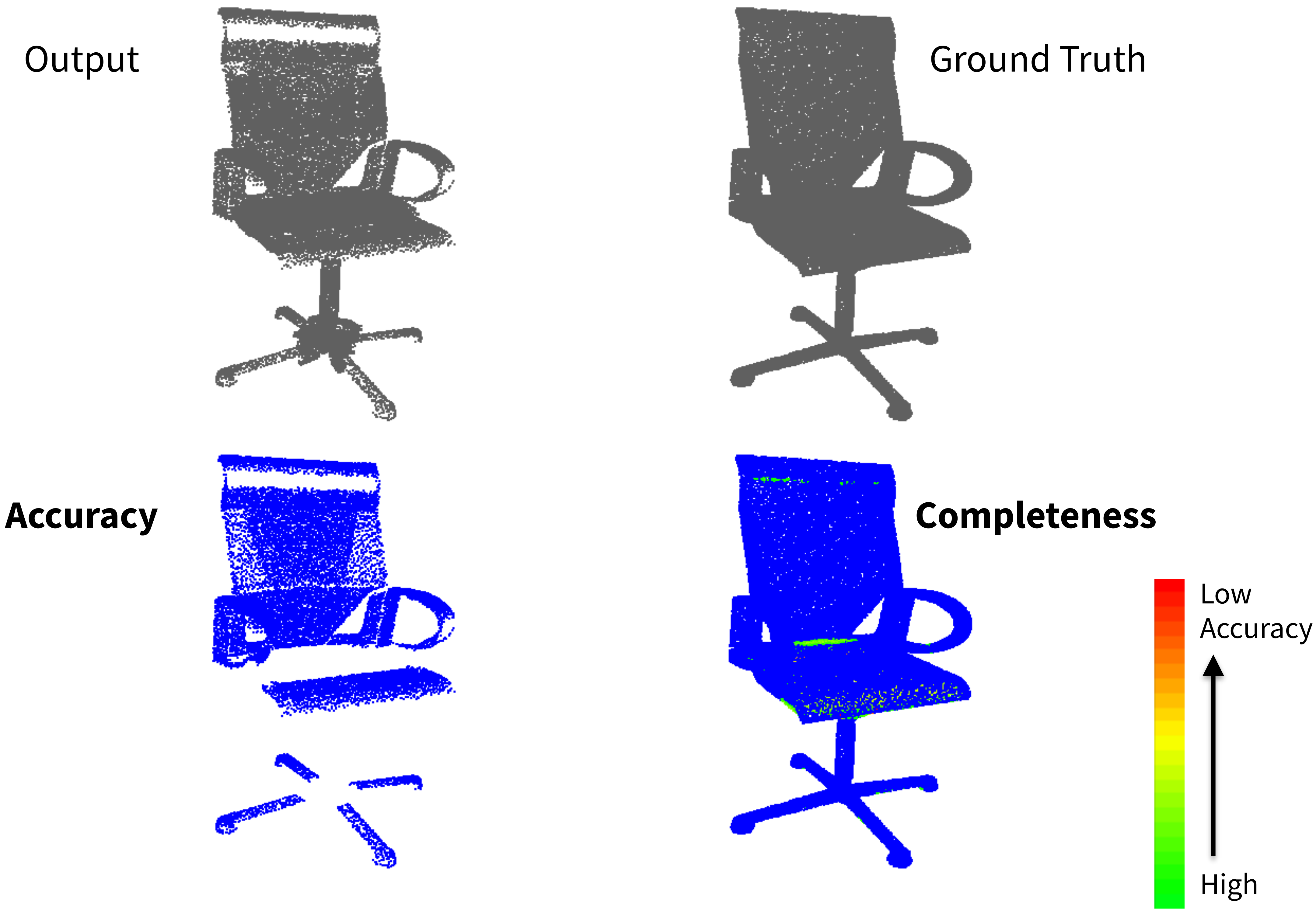


Scene Completion





Evaluation



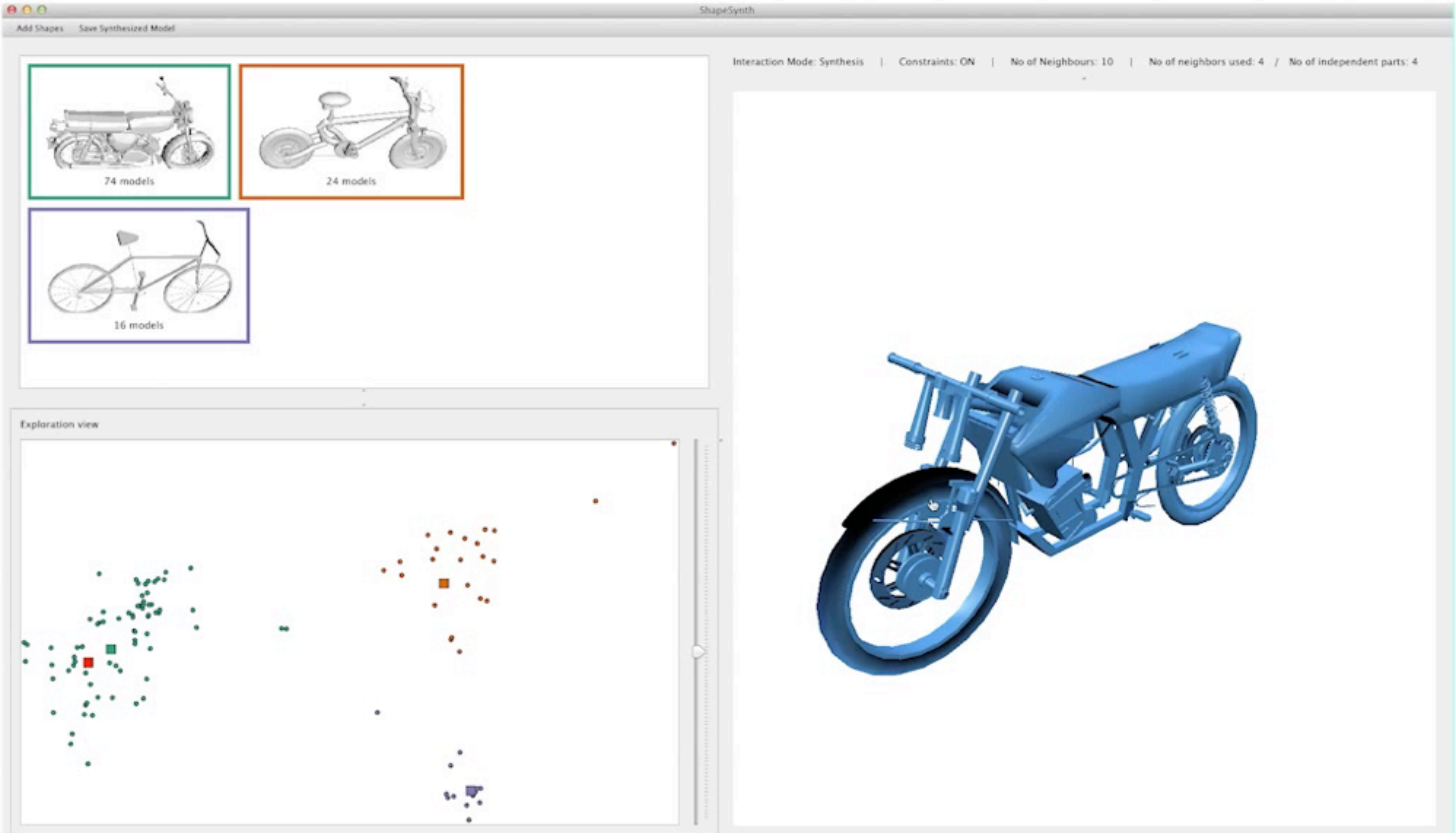
Output
Ground Truth
Accuracy
Completeness
Low
Accuracy
High

Comparisons

	Accuracy	Completeness
Shape Completion		
Ours	85%	**78%**
[Podolak'06] (symmetry)	**99%**	69%
[Shen'12] (closest parts)	62%	60%
Scene Completion		
Ours	**62%**	**82%**
[Gupta'15] (closest object)	57%	52%

Exploration & Synthesis

Using part-based templates for synthesis


ShapeSynth
Add Shapes
Save Synthesized Model
Interaction Mode: Synthesis | Constraints: ON | No of Neighbours: 10 | No of neighbors used: 4 / No of independent parts: 4
74 models
24 models
16 models
Exploration view

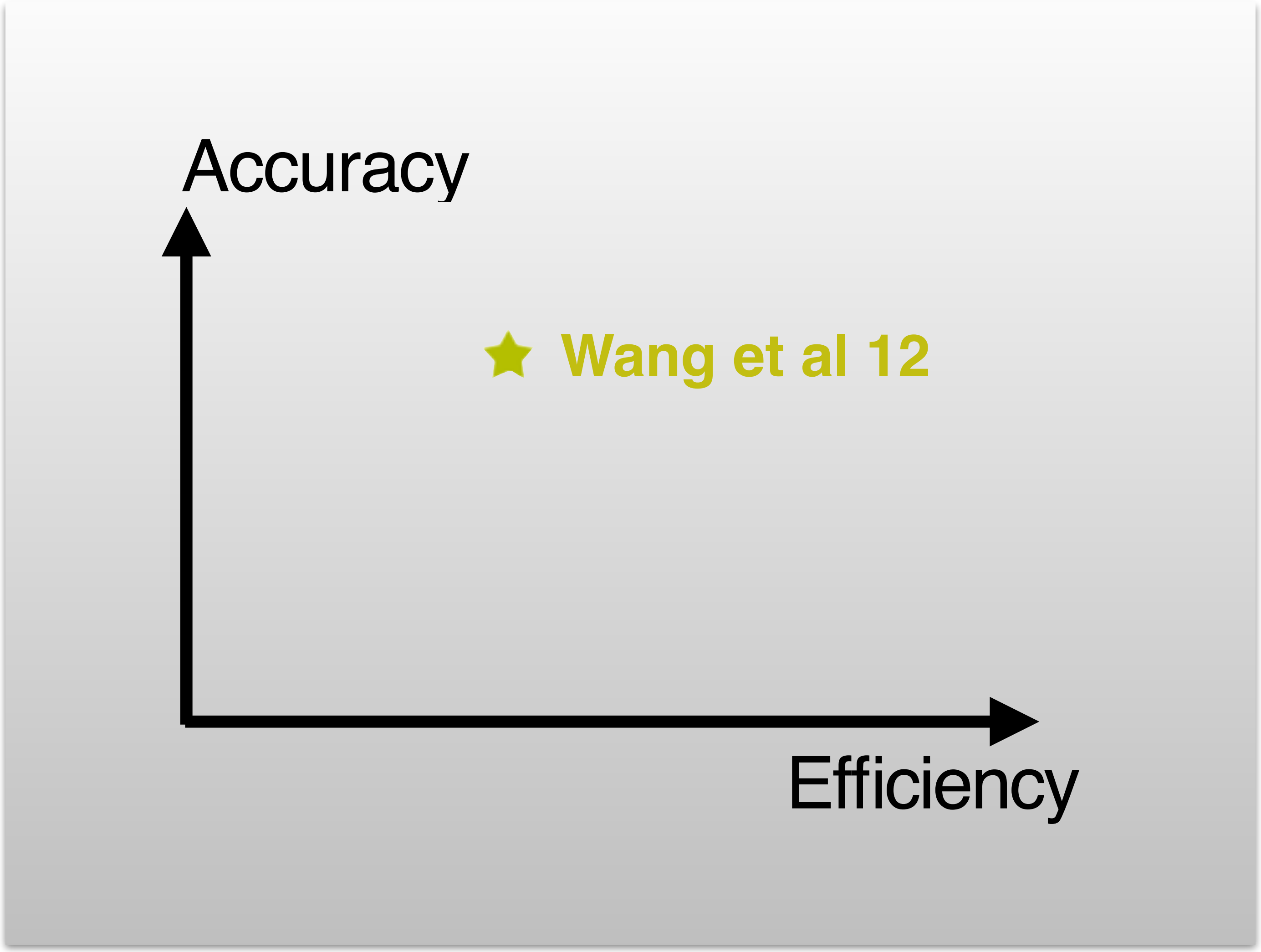
Training Data

Where do we get segmented shapes?

Training Data

Where do we get segmented shapes?

- Active learning for labeling [Wang'12]
    - Dataset: 1090 meshes, 2-5 parts per mesh, watertight manifold



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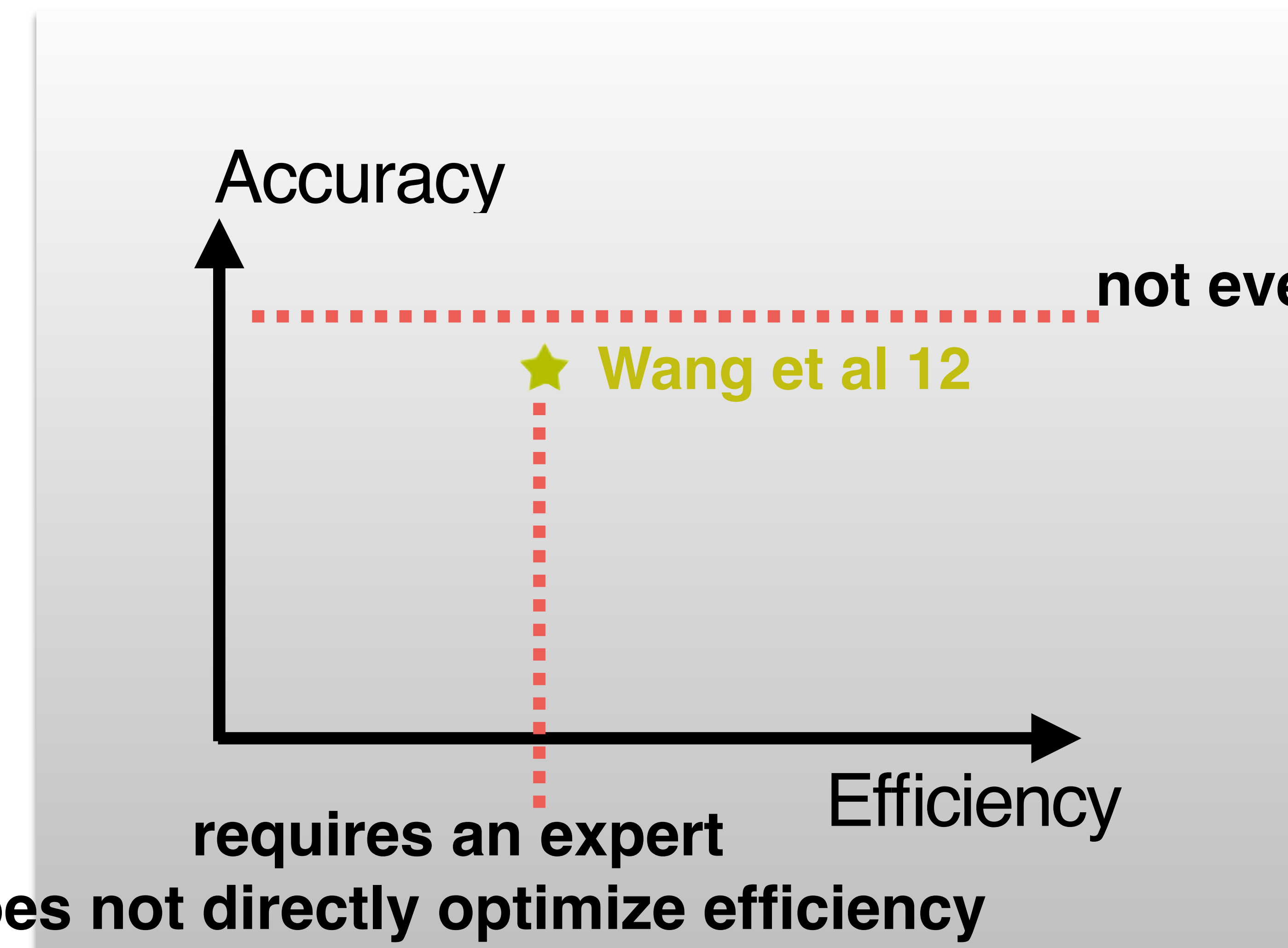


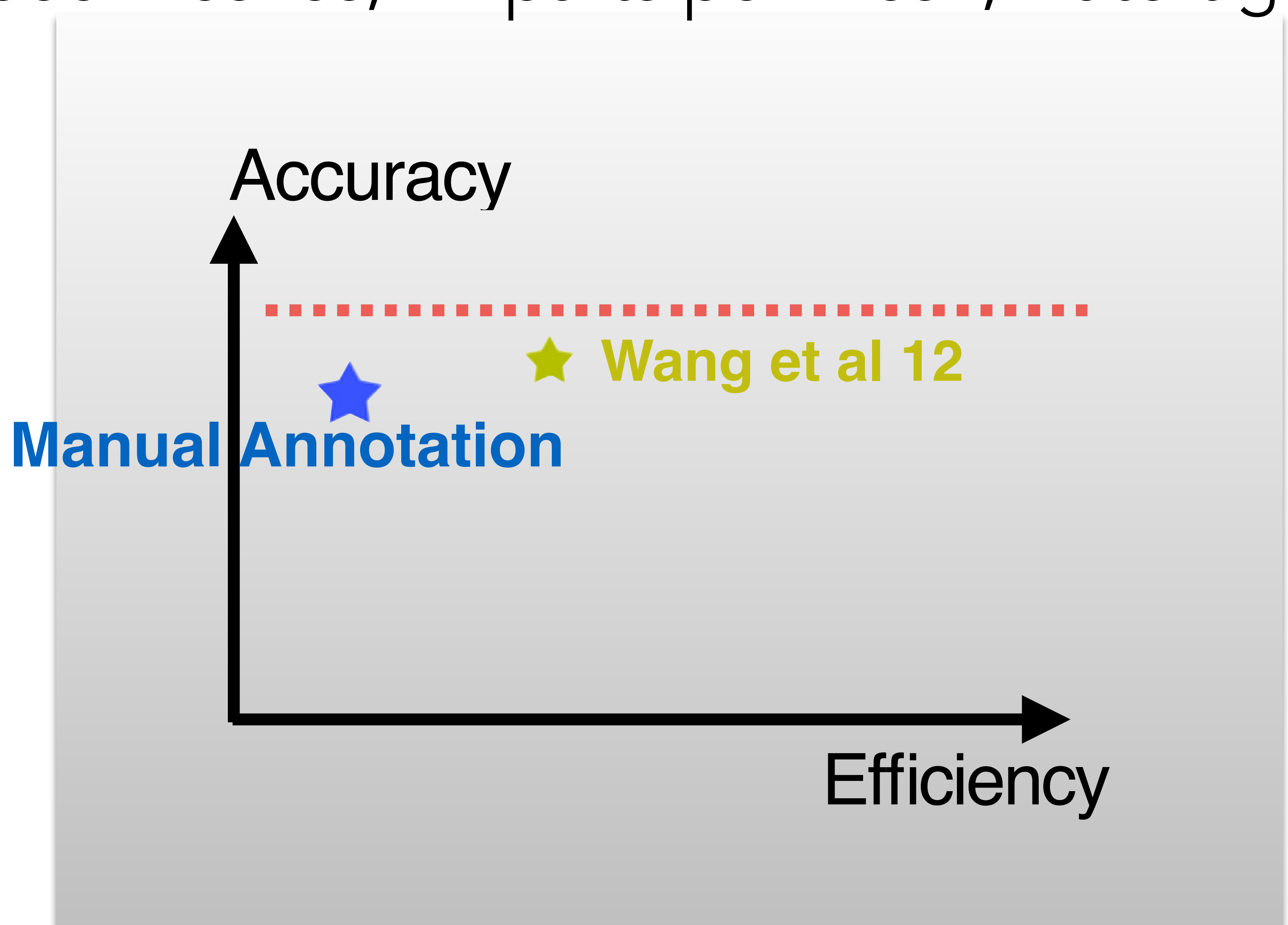
not every model is verified by a human

does not directly optimize efficiency
(active learning objective: train the best classifier)

Training Data

Where do we get segmented shapes?

- Active learning for labeling [Wang'12]
  - Dataset: 1090 meshes, 2-5 parts per mesh, watertight manifold
- Manual annotation [Chen'09]
  - Dataset: 380 meshes, 19 parts per mesh, watertight manifold



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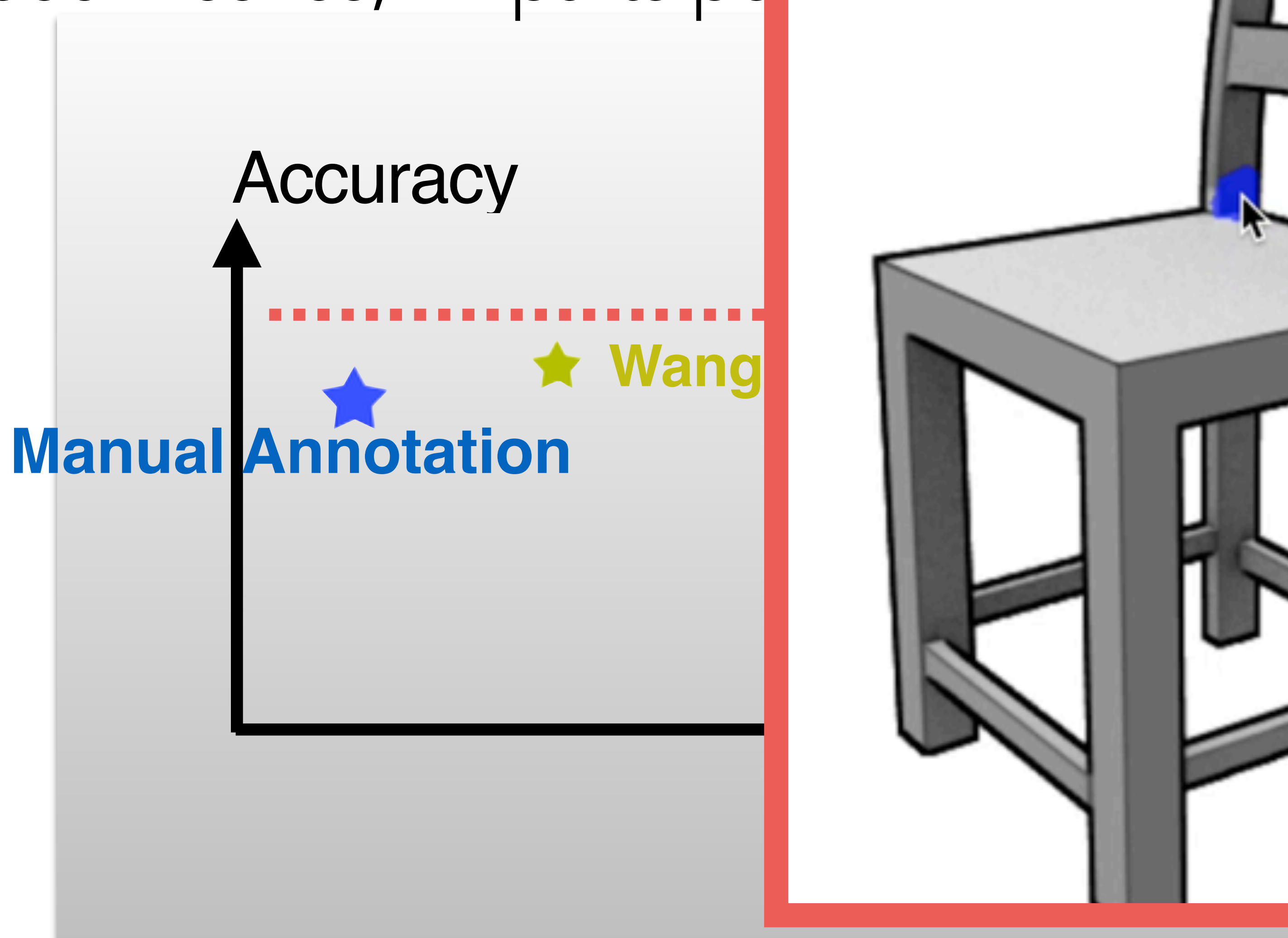

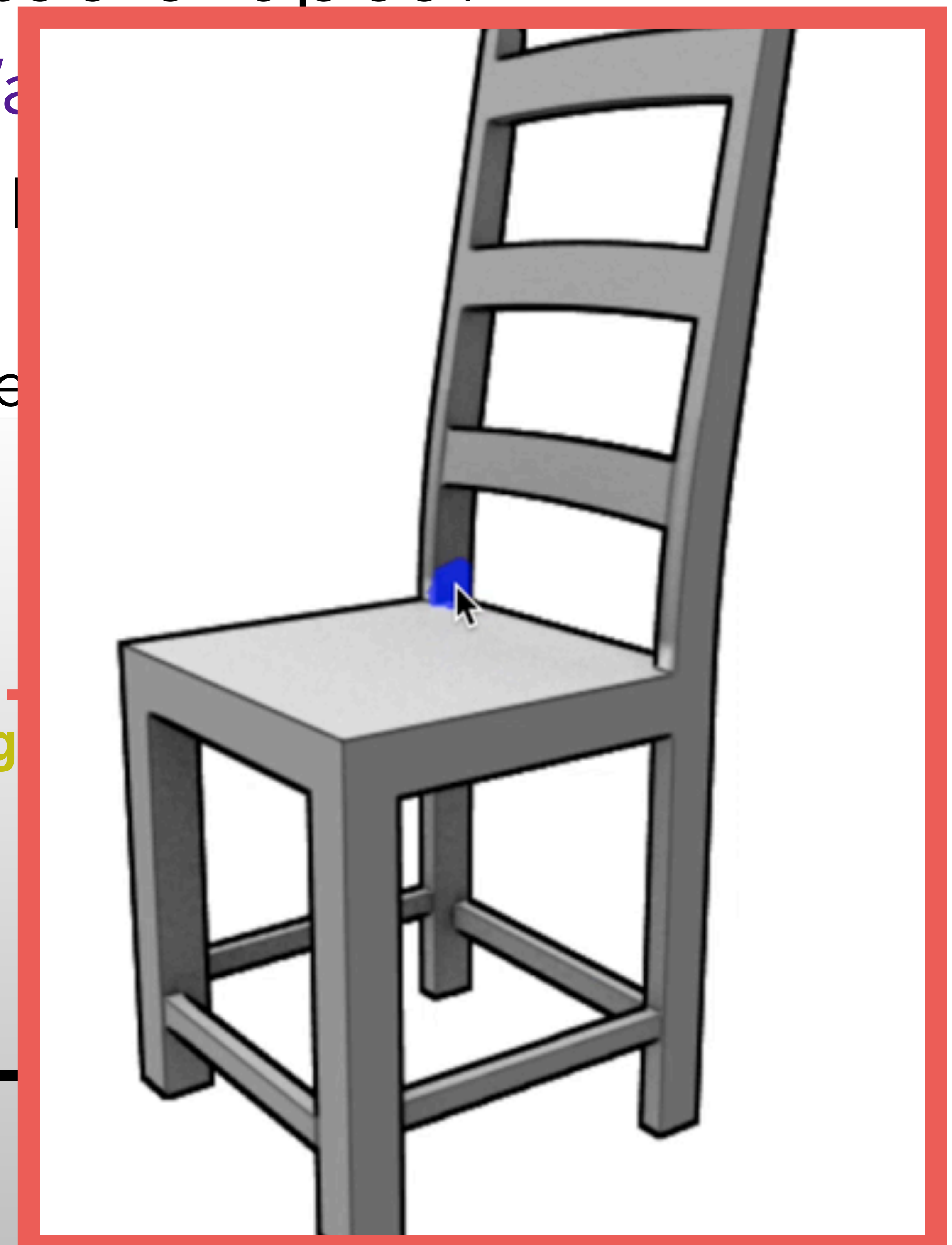

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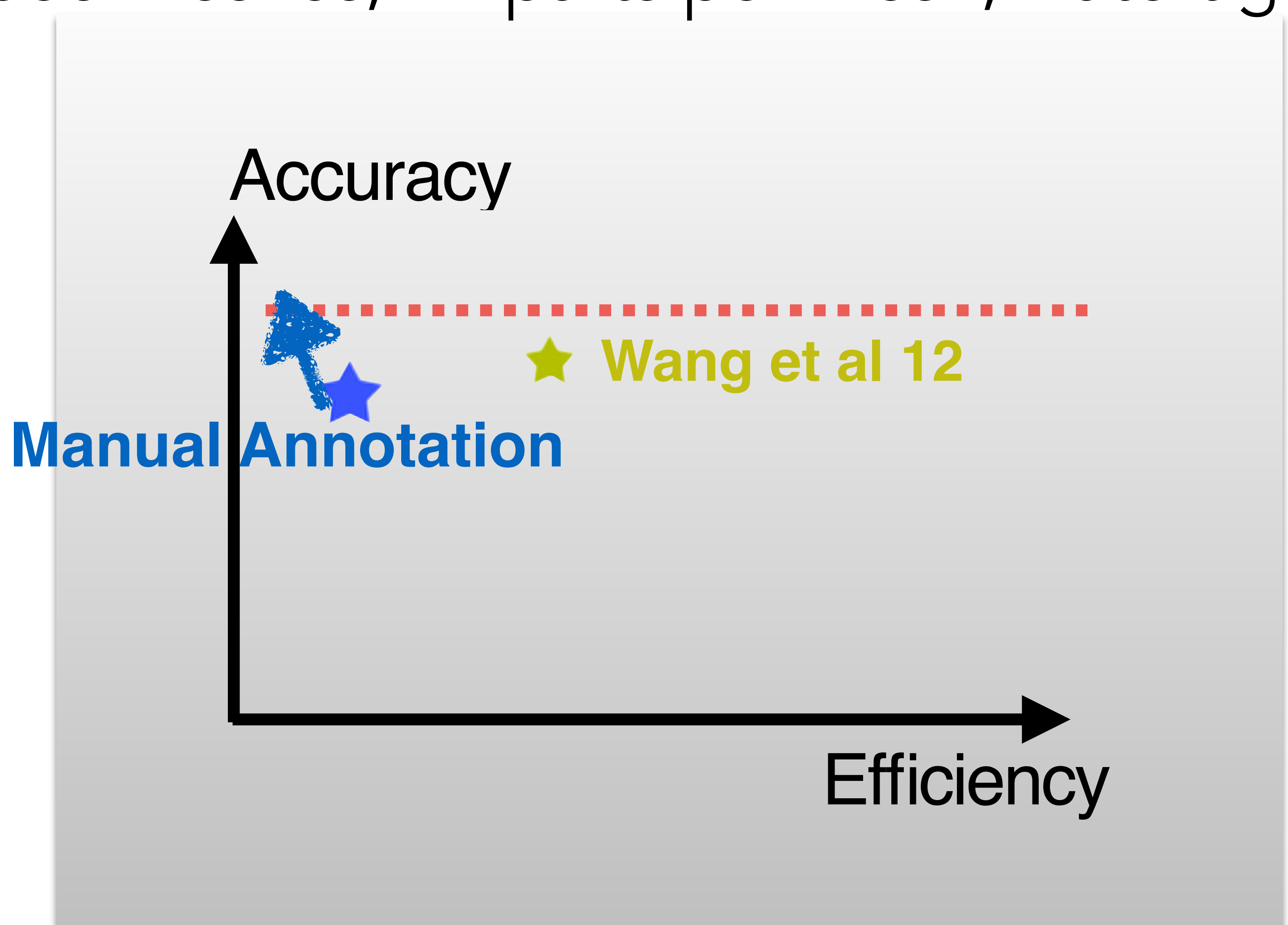
Verify all results!



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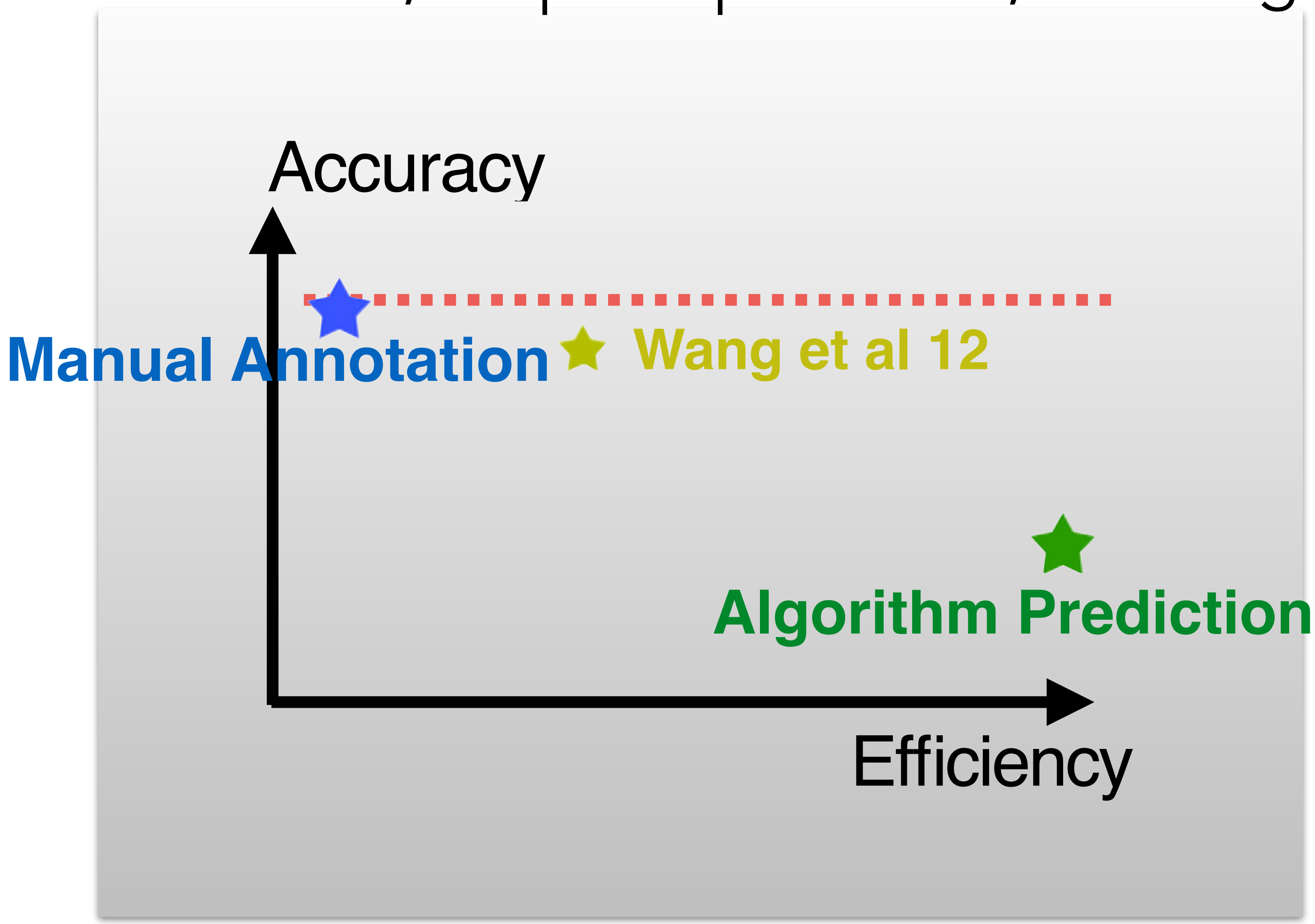
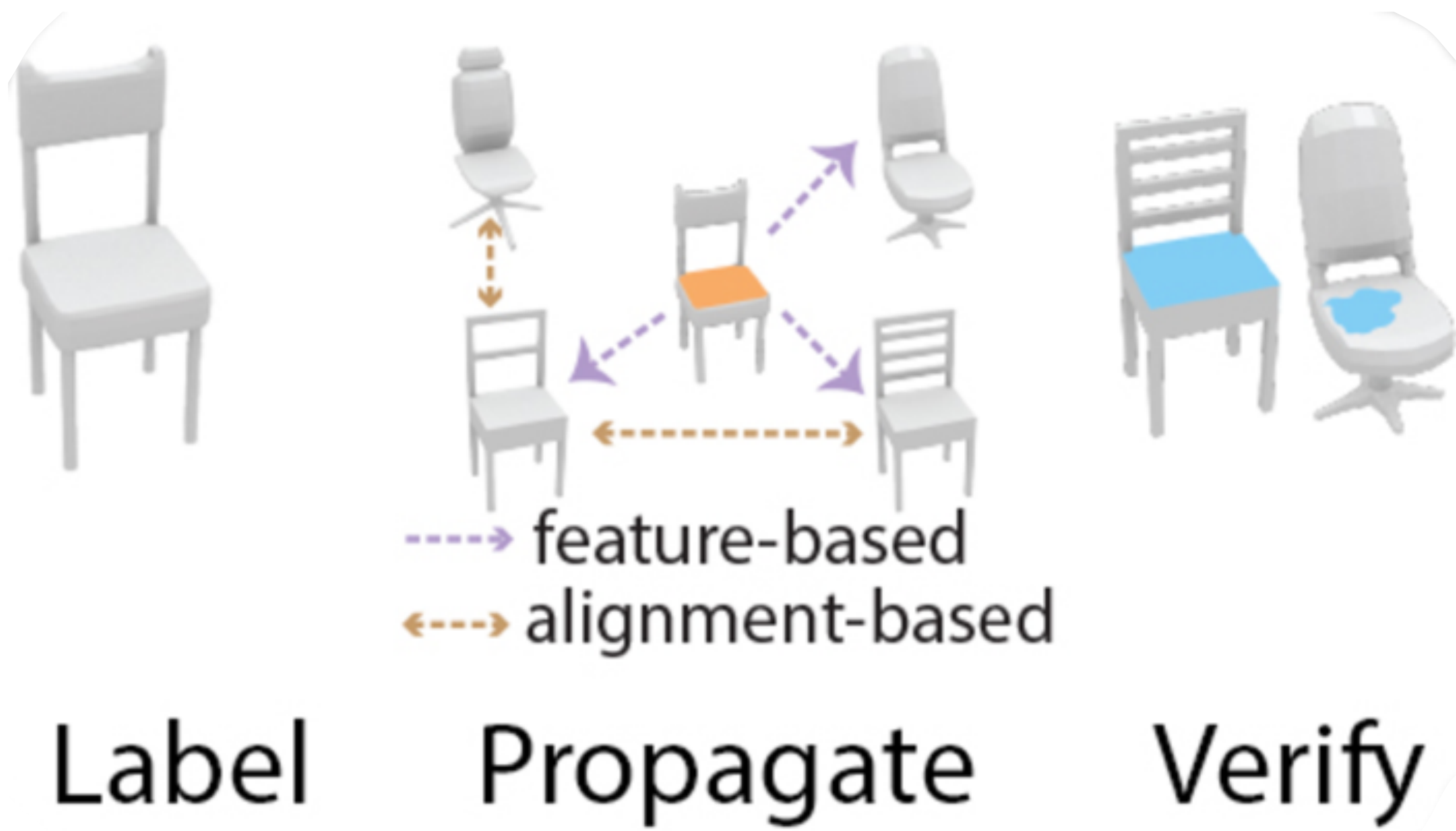
- Manual annotation [Chen'09]
  - Dataset: 380 meshes, 19 parts per mesh, watertight manifold



Our Approach

Verify algorithmic predictions



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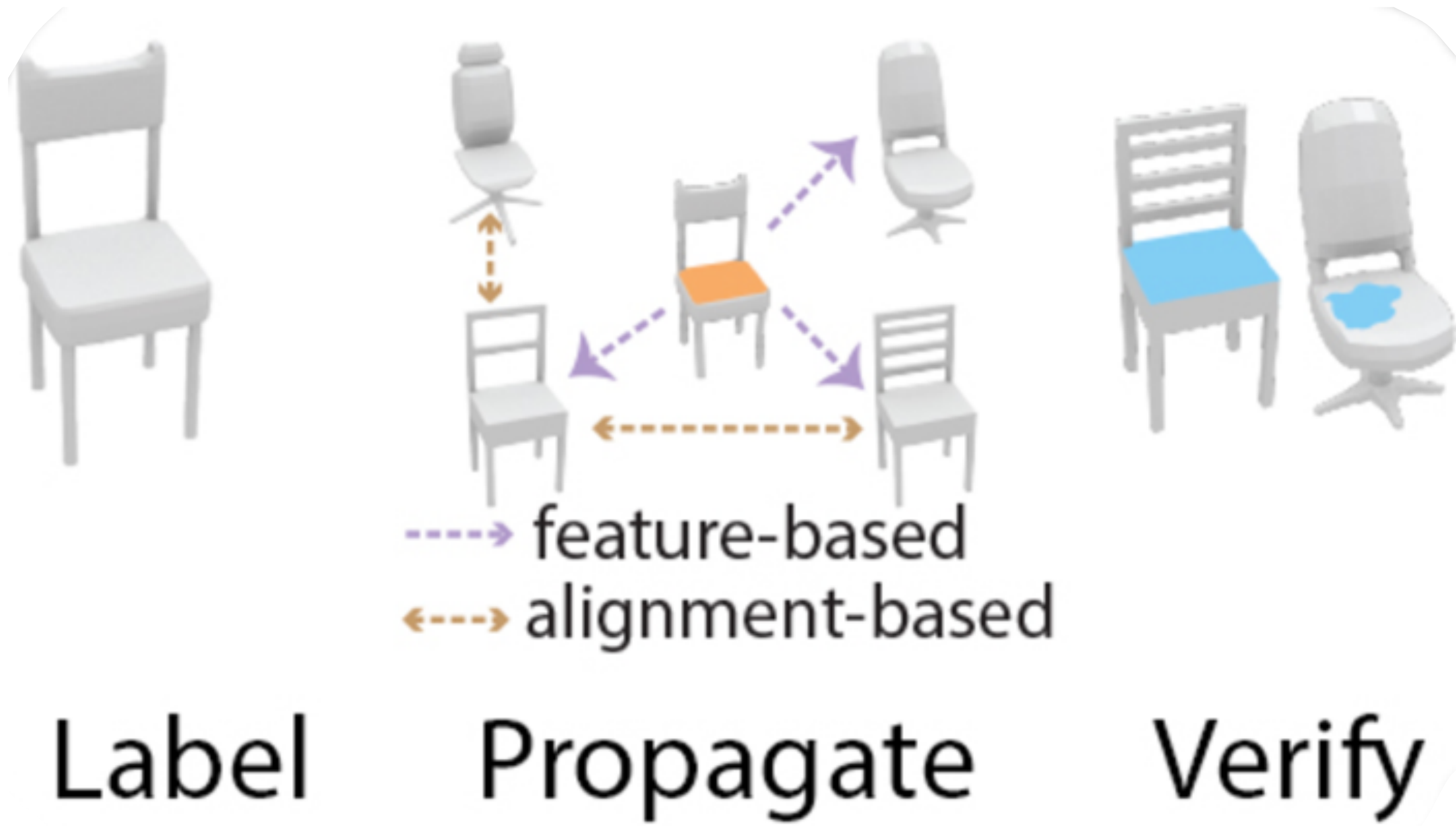
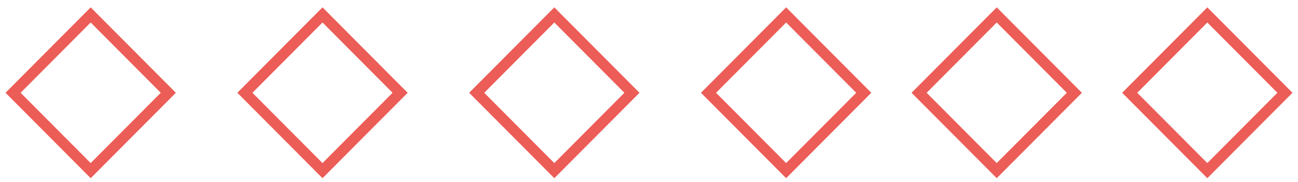


Which models to label & which labels to verify?

Utility Function

several shapes



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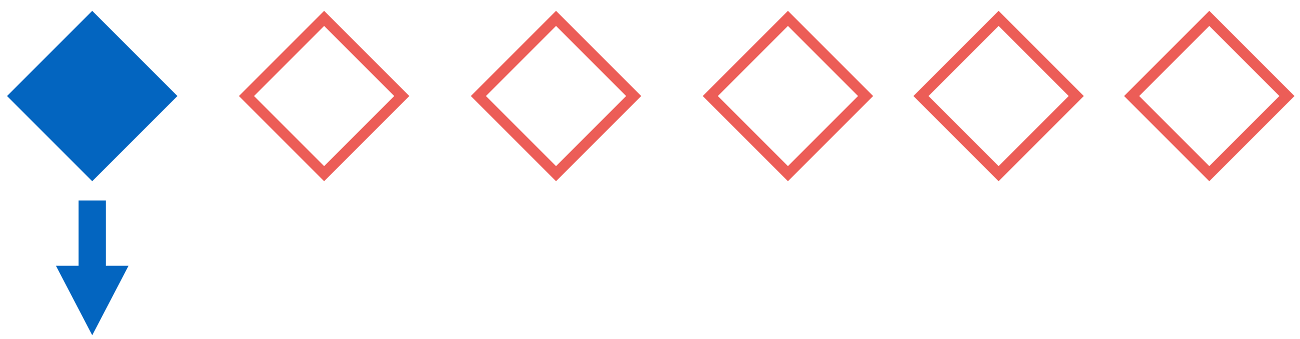
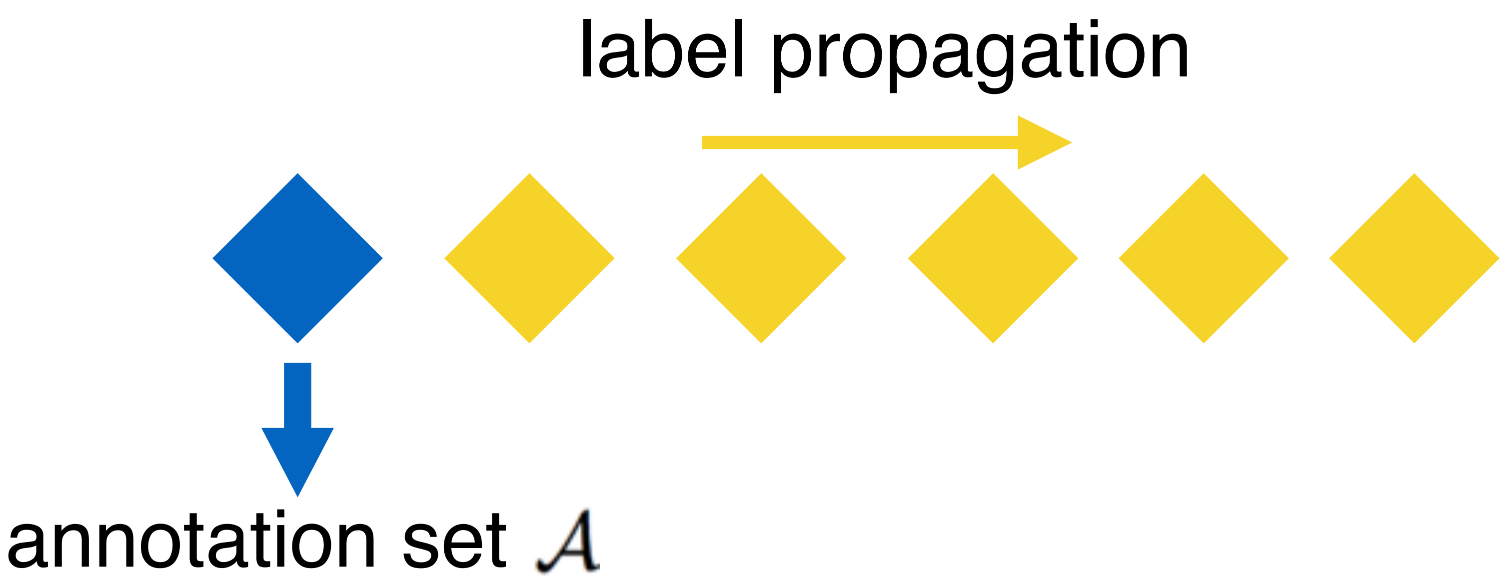


annotation set $\mathcal{A}$

Utility Function



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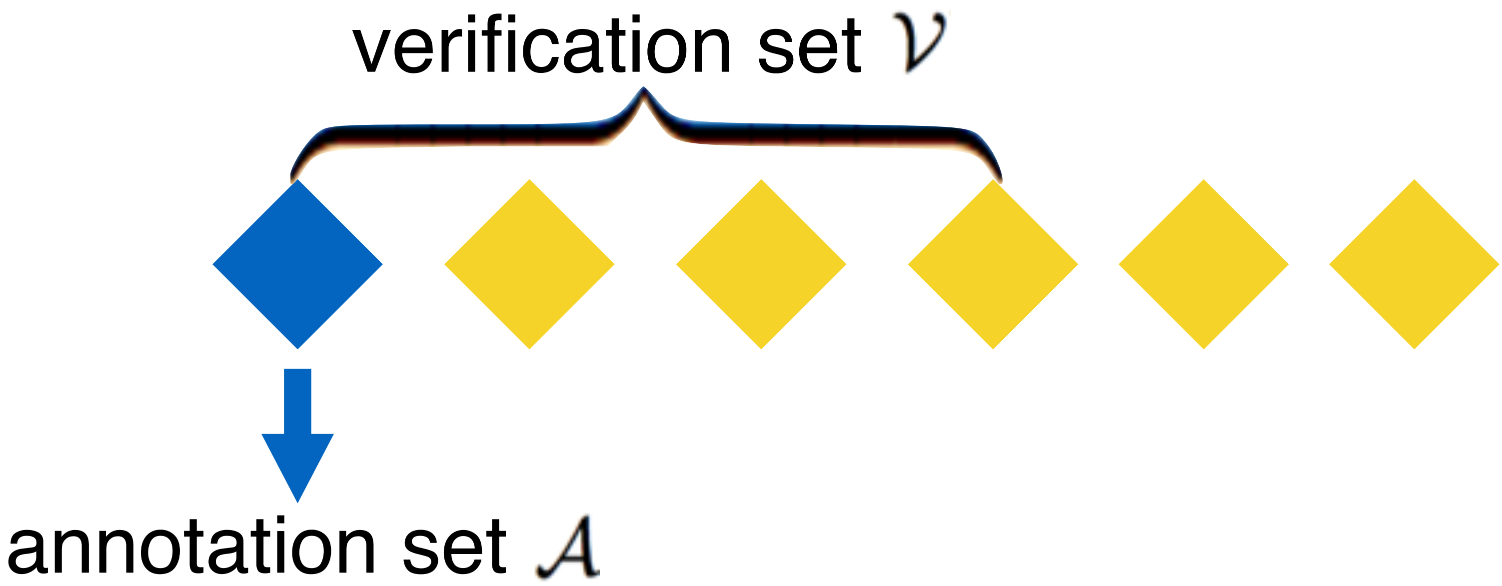

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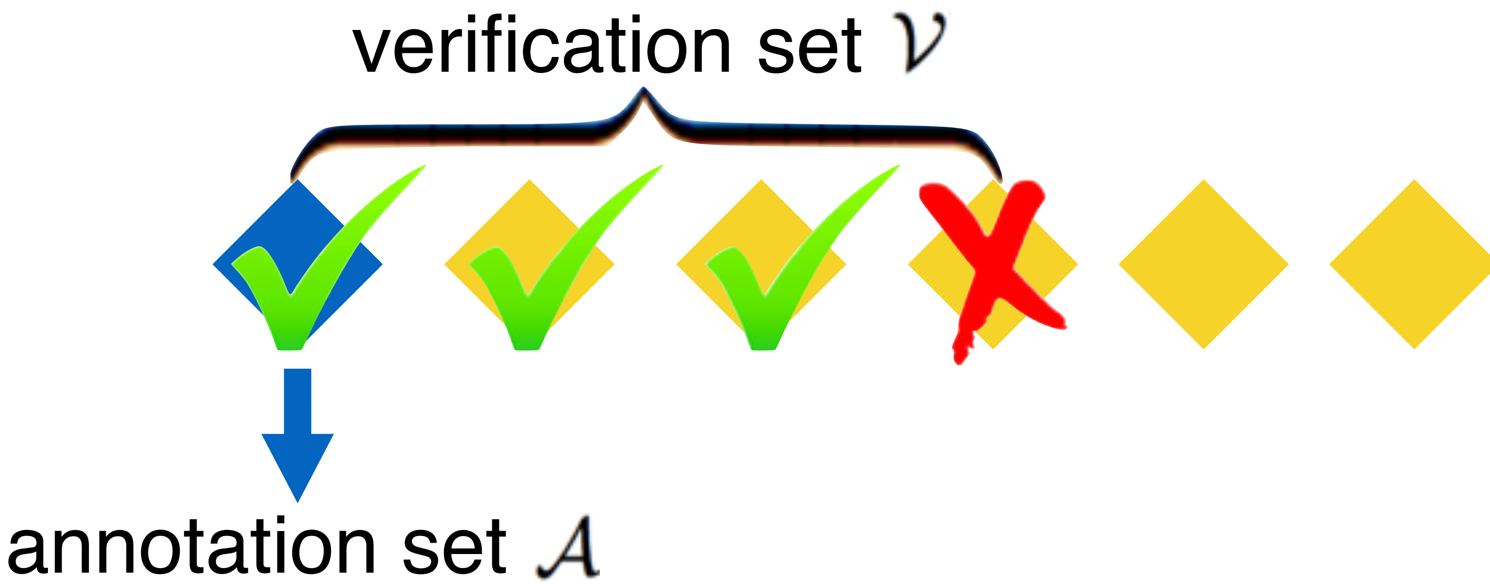

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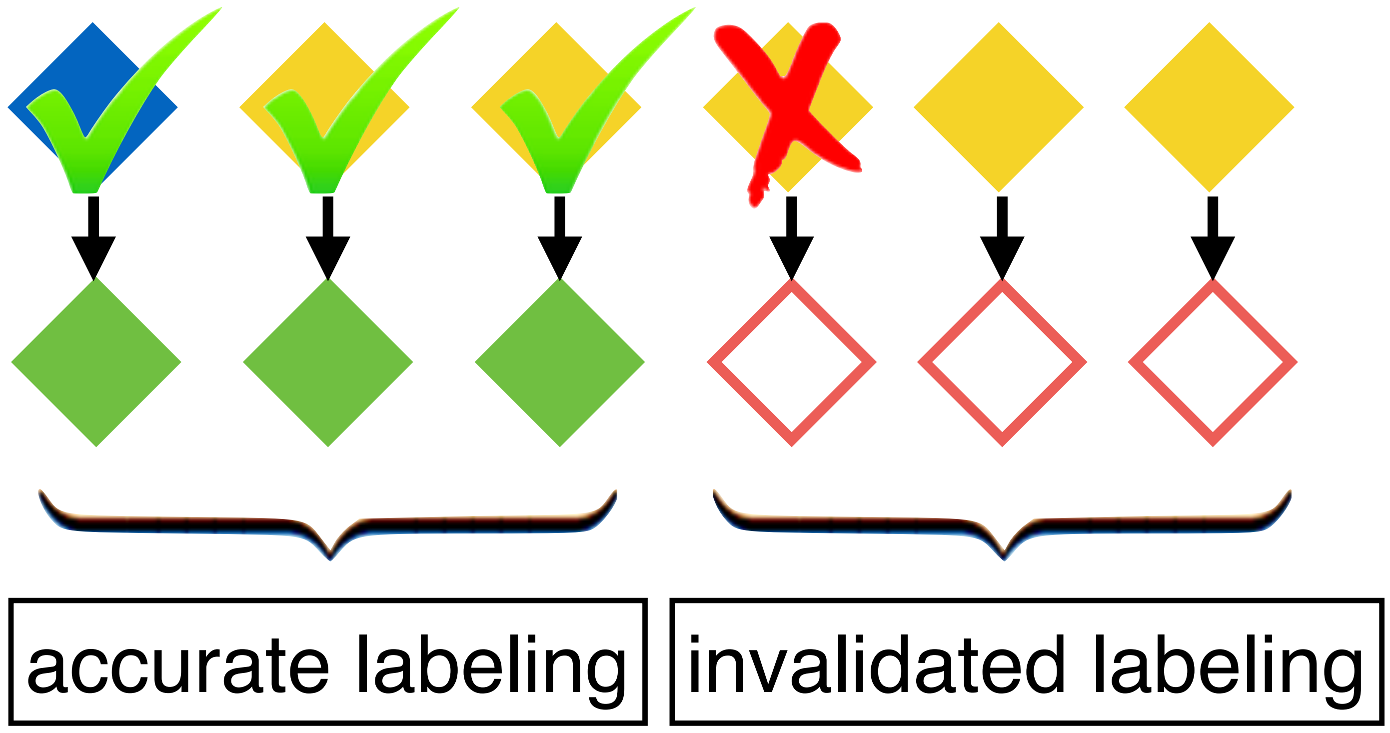

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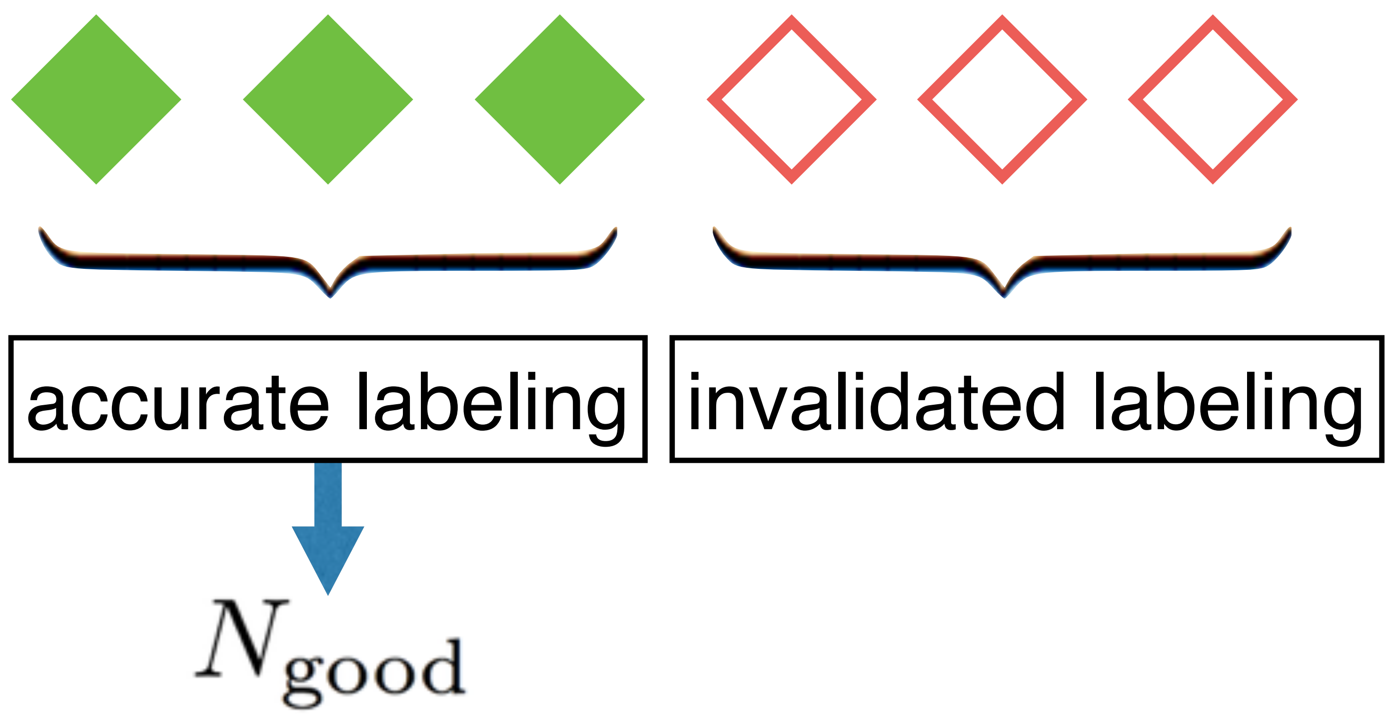

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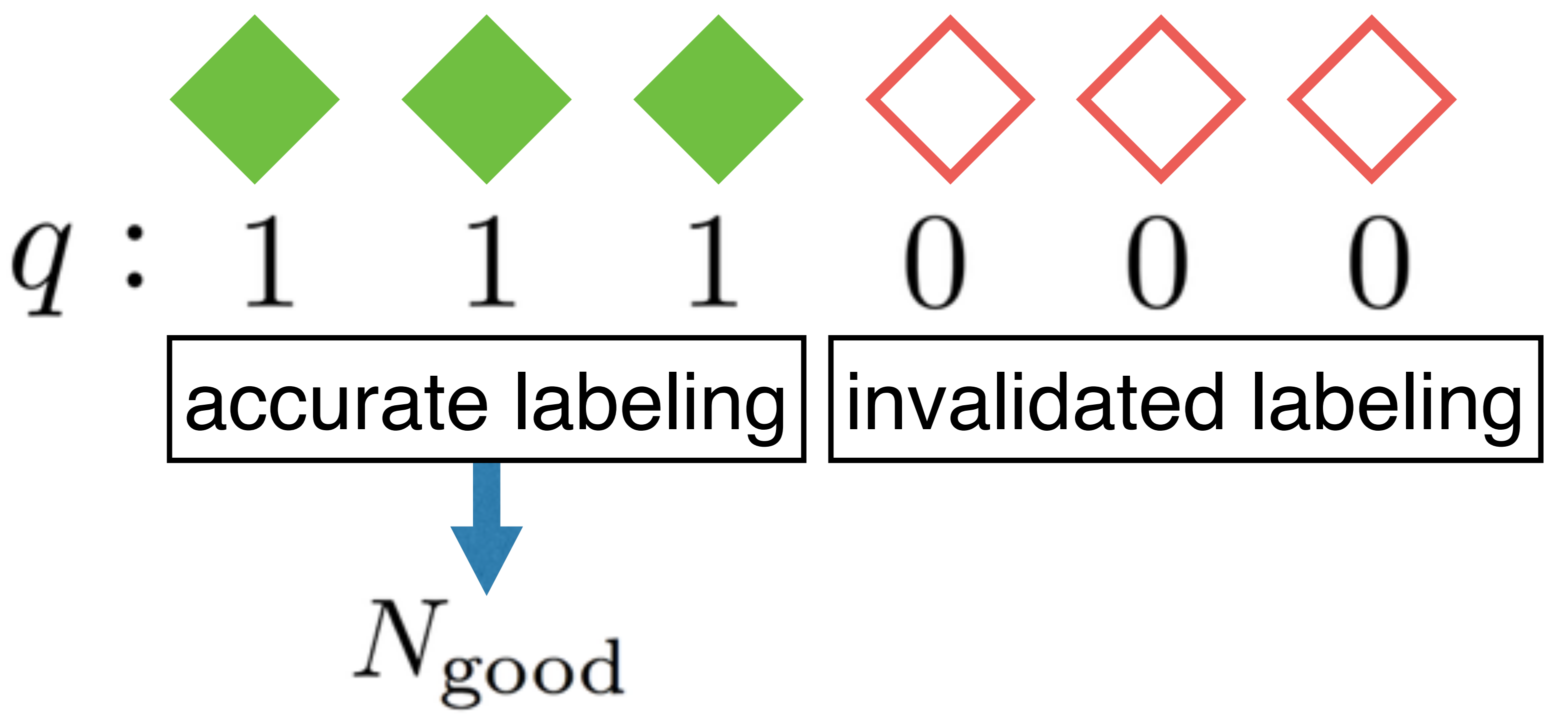

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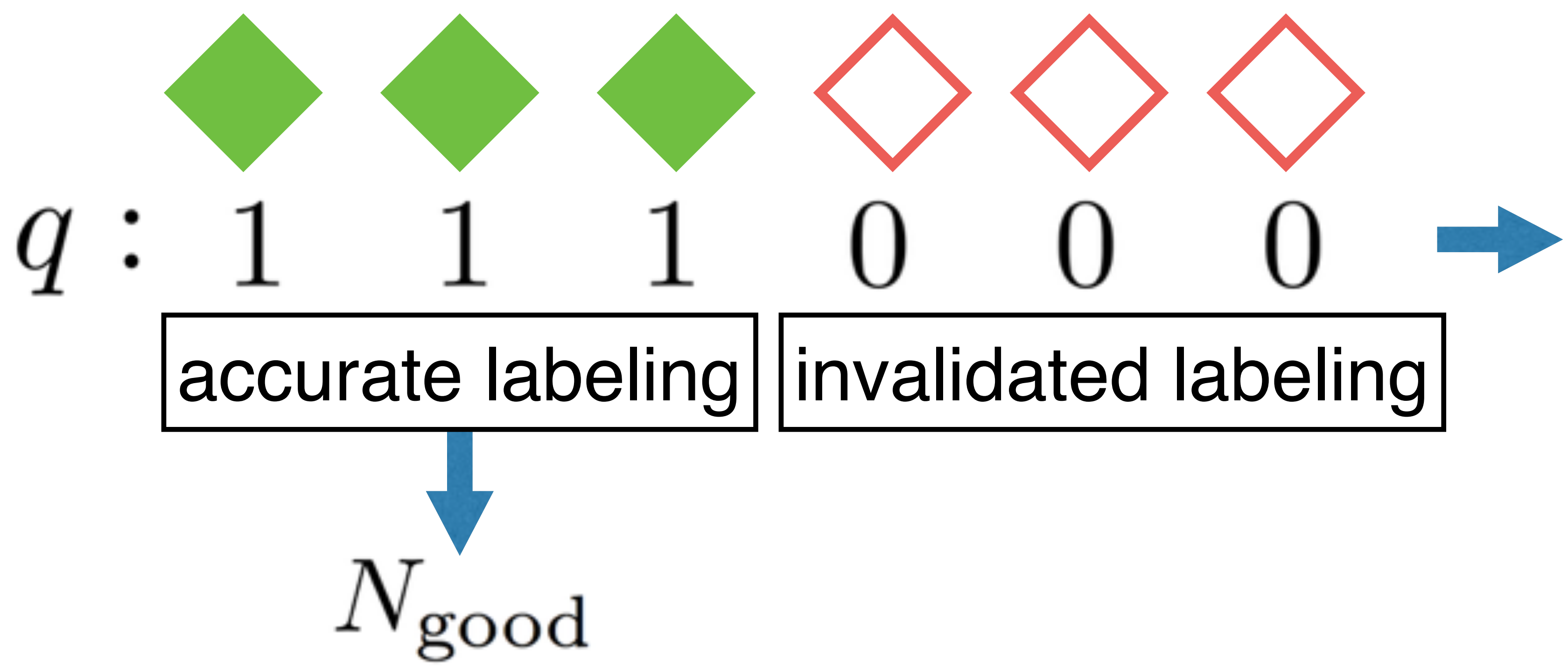
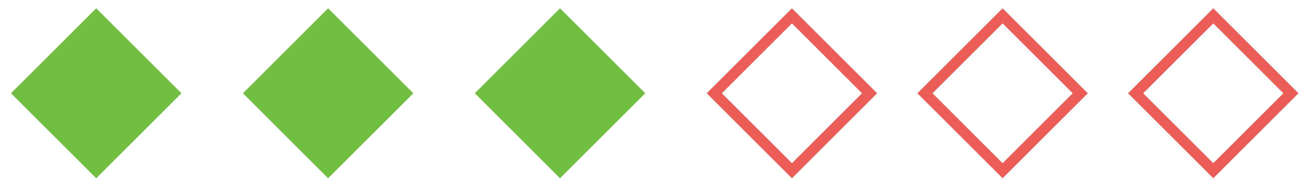


A function of
annotation set $\mathcal{A}$
and verification set $\mathcal{V}$

Utility Function



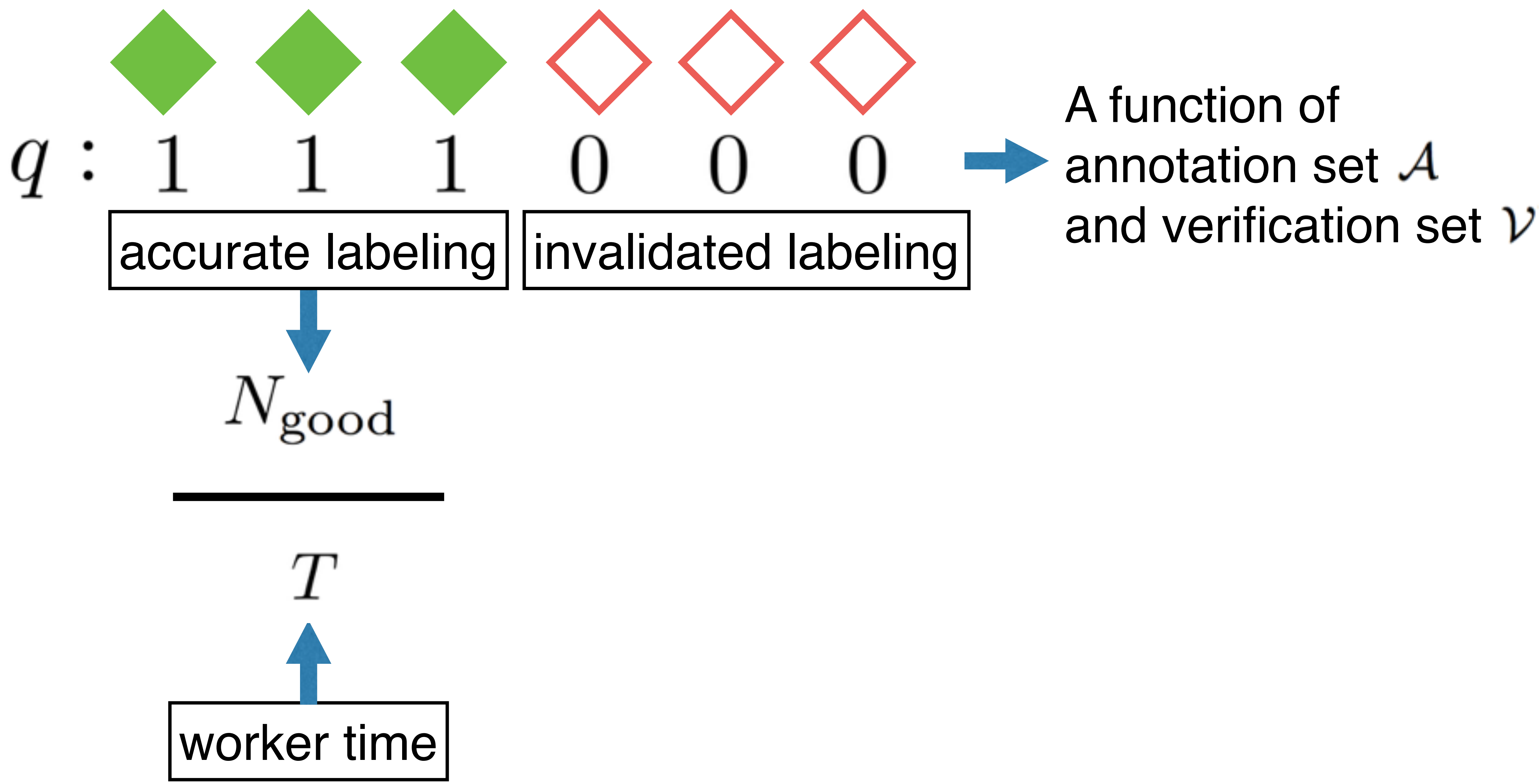
$q: 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0$

accurate labeling | invalidated labeling

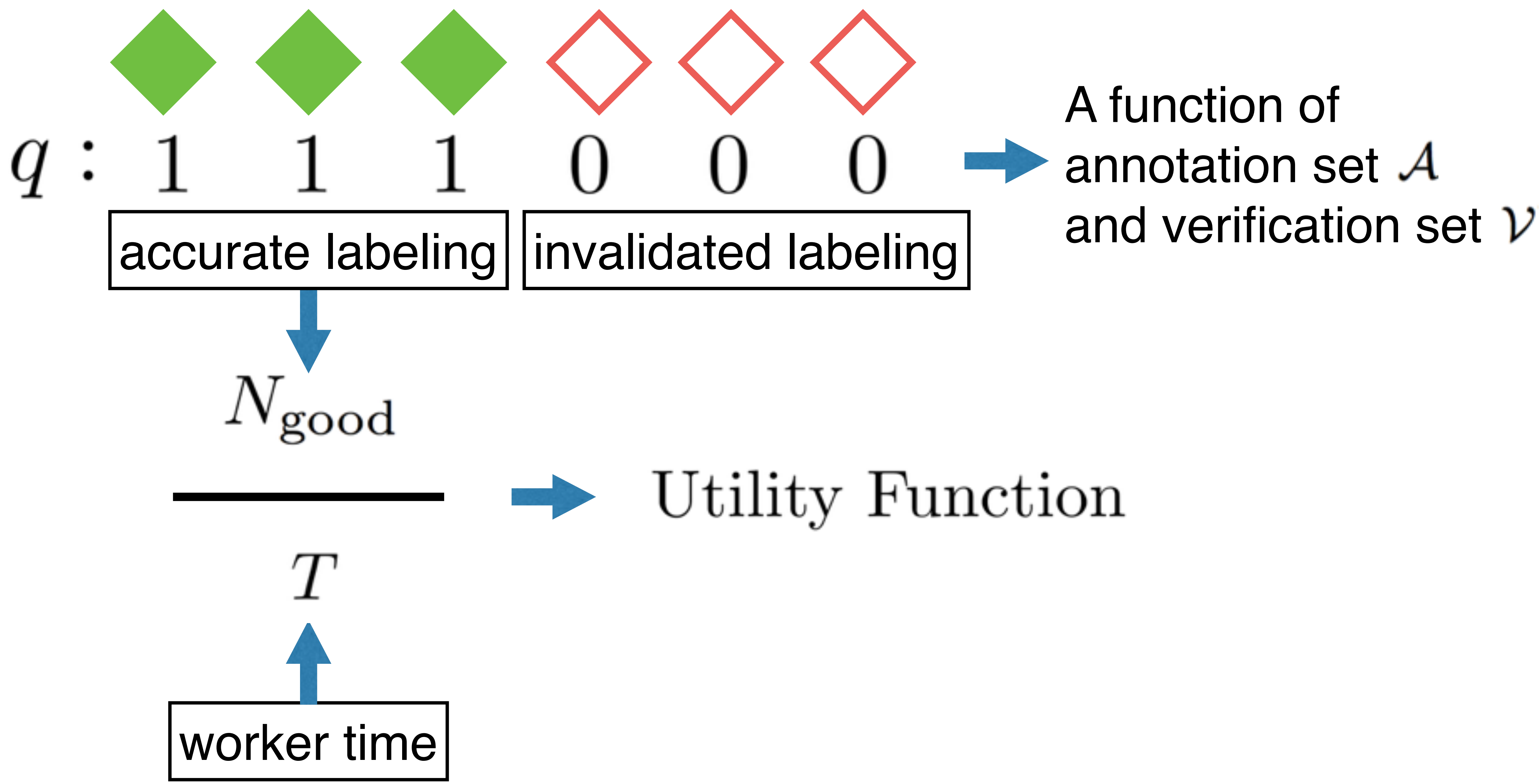
A function of annotation set $\mathcal{A}$ and verification set $\mathcal{V}$

$$N_{\text{good}} = \sum q(\mathcal{A}, \mathcal{V})$$

Utility Function



Utility Function



Utility Function

$$T = t_{\text{annotation}}(\mathcal{A}) + t_{\text{verification}}(\mathcal{V}, \{q\})$$

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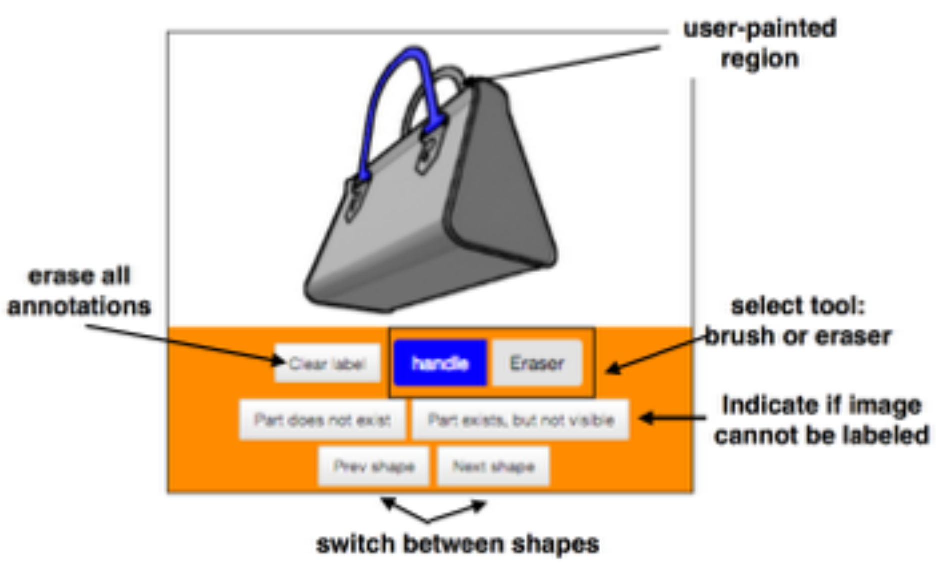

$$\tau_{\text{annotation}} \approx 30s/\text{label}$$

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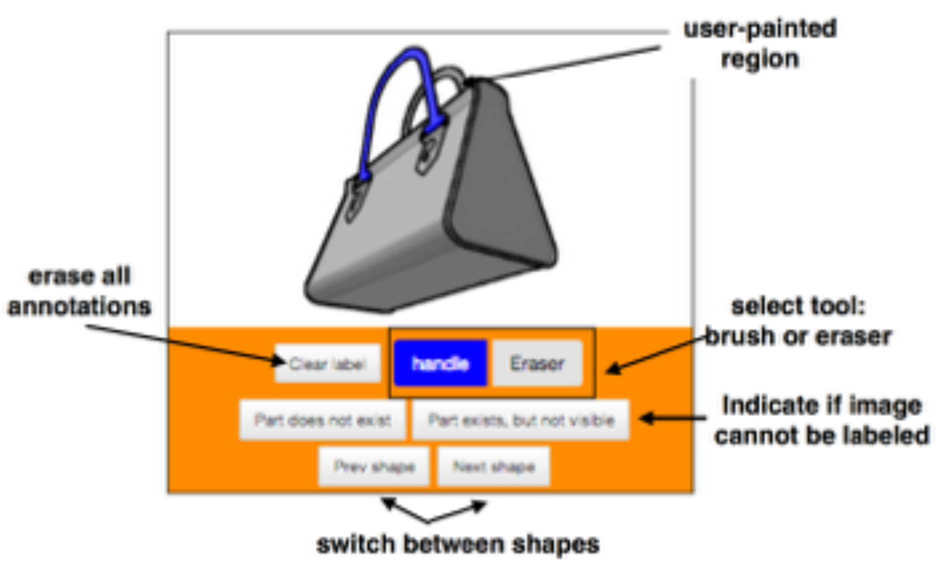

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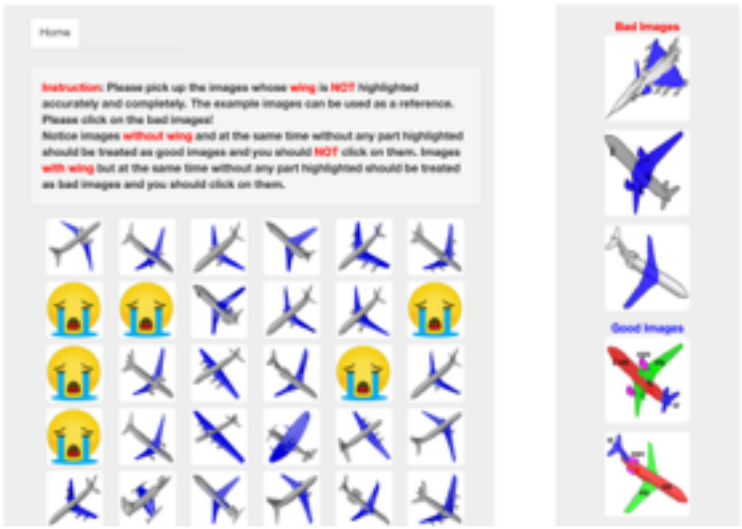

$$\tau_{\text{identification}} \approx 0.3s/\text{label}$$

$$\tau_{\text{click}} \approx 1.1s/\text{label}$$

Utility Function

$$\frac{N_{\text{good}}}{T}$$

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$$\boxed{\frac{\mathbb{E}[N_{\text{good}}]}{\mathbb{E}[T]}}$$

Algorithm behavior

Utility Function

$$\operatorname*{argmin}_{\mathcal{A},\mathcal{V}} \frac{\mathbb{E}[N_{\mathbf{good}}]}{\mathbb{E}[T]}$$

Utility Function

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

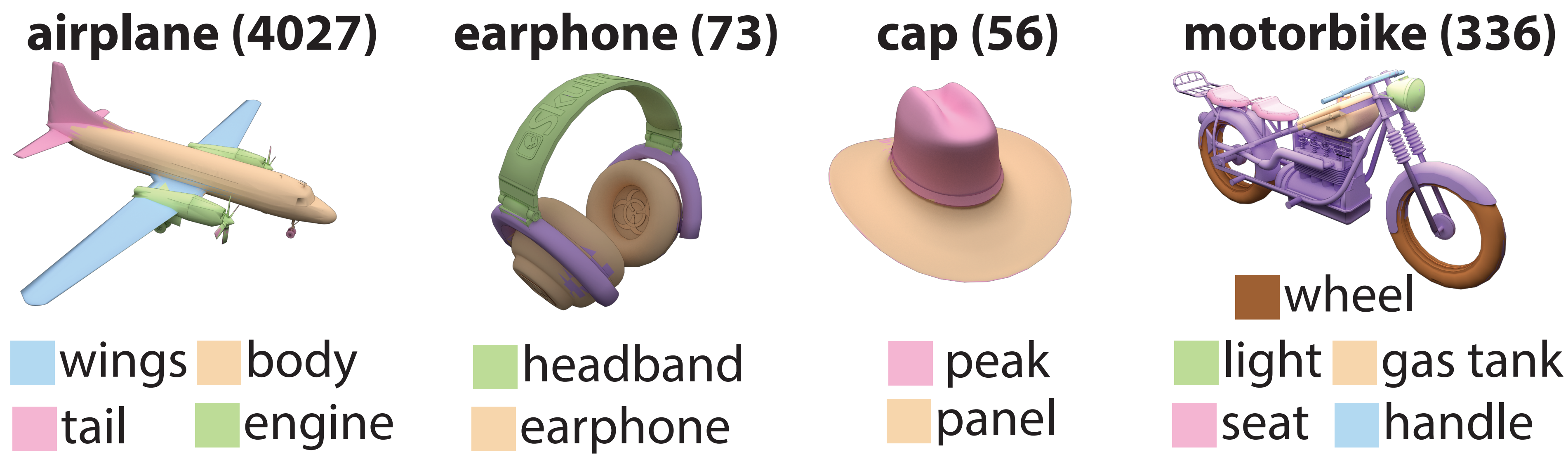
Select Annotation Set: ***Beam Search***

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

Results

Dataset

- 30,000 shapes
- 90,000 parts



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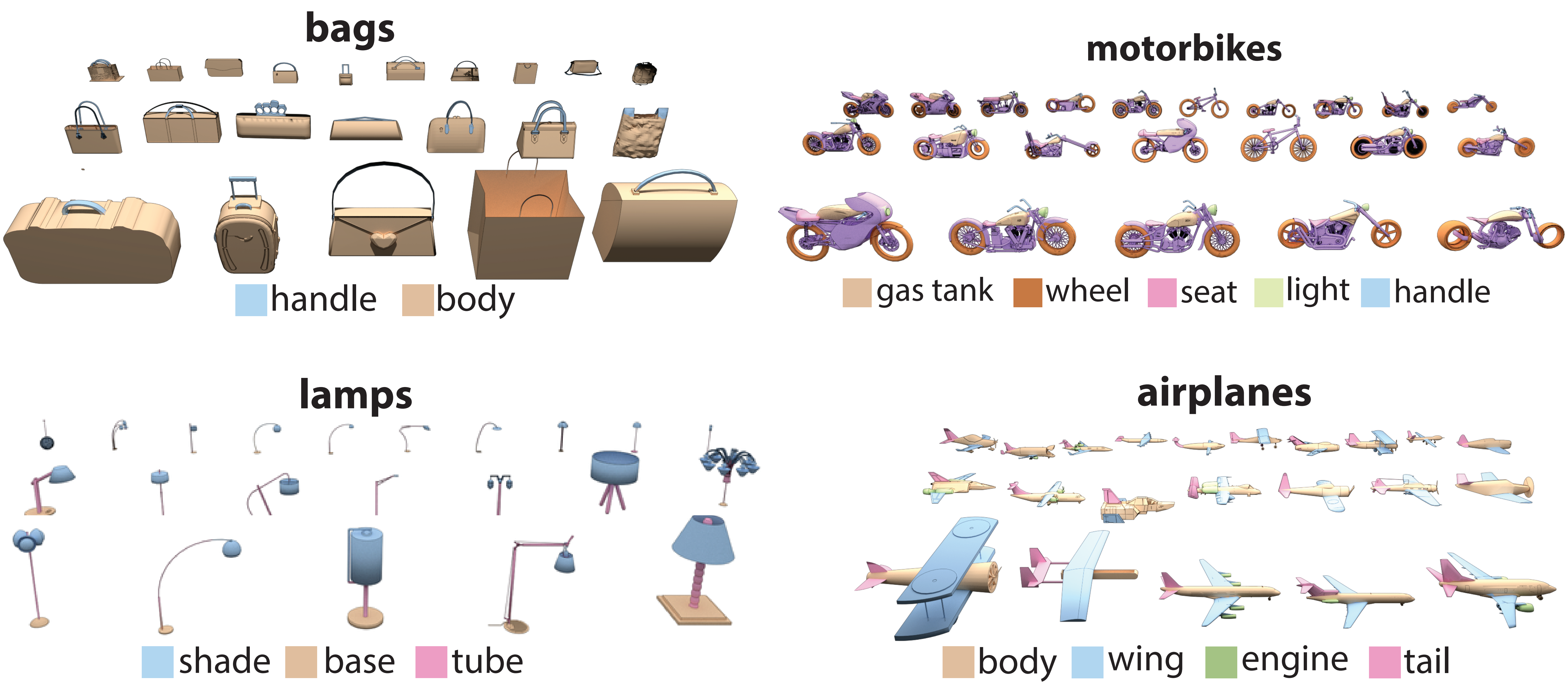

Time Saving

Comparison on manifold shapes

- Chen'09 (manual) : about x12 more expensive
- Wang'12 (active) : about x2 more expensive

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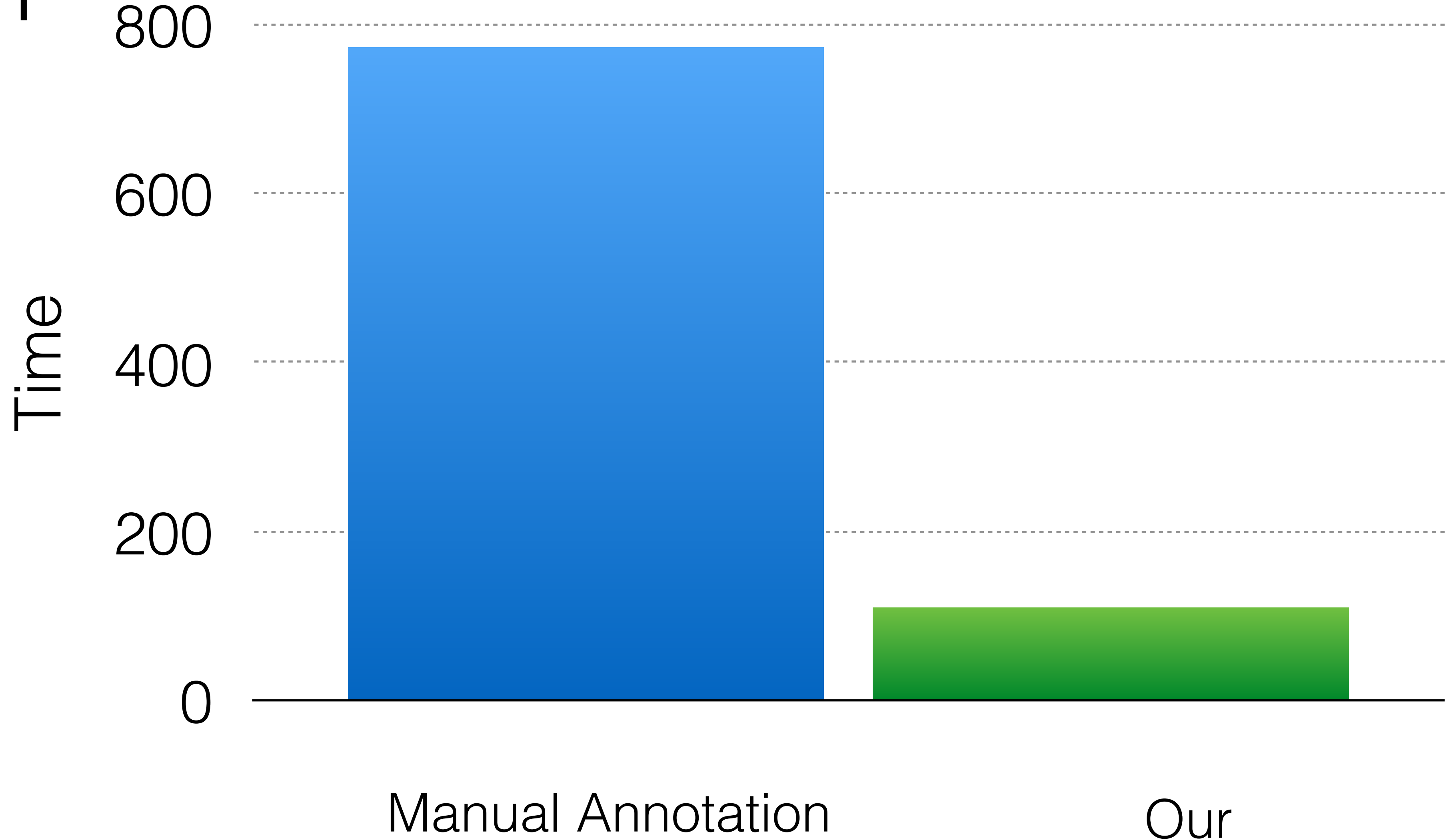
Comparison on data "in the wild"



Summary

Large collections of 3D models are available (and more are coming!)

- 3D modeling repositories
- 3D printing datasets
- Kinect scans
- Laser scans of cities,
- Online shopping catalogues
- Medical imaging data
- Protein databases
- …

Summary

Large collections of 3D models are available (and more are coming!)

Part-based models are powerful, but need data

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Large collections of 3D models are available (and more are coming!)

Part-based models are powerful, but need data

Getting verified results might save you time

- if you verify automatic labels

Future Work

Beyond geometry

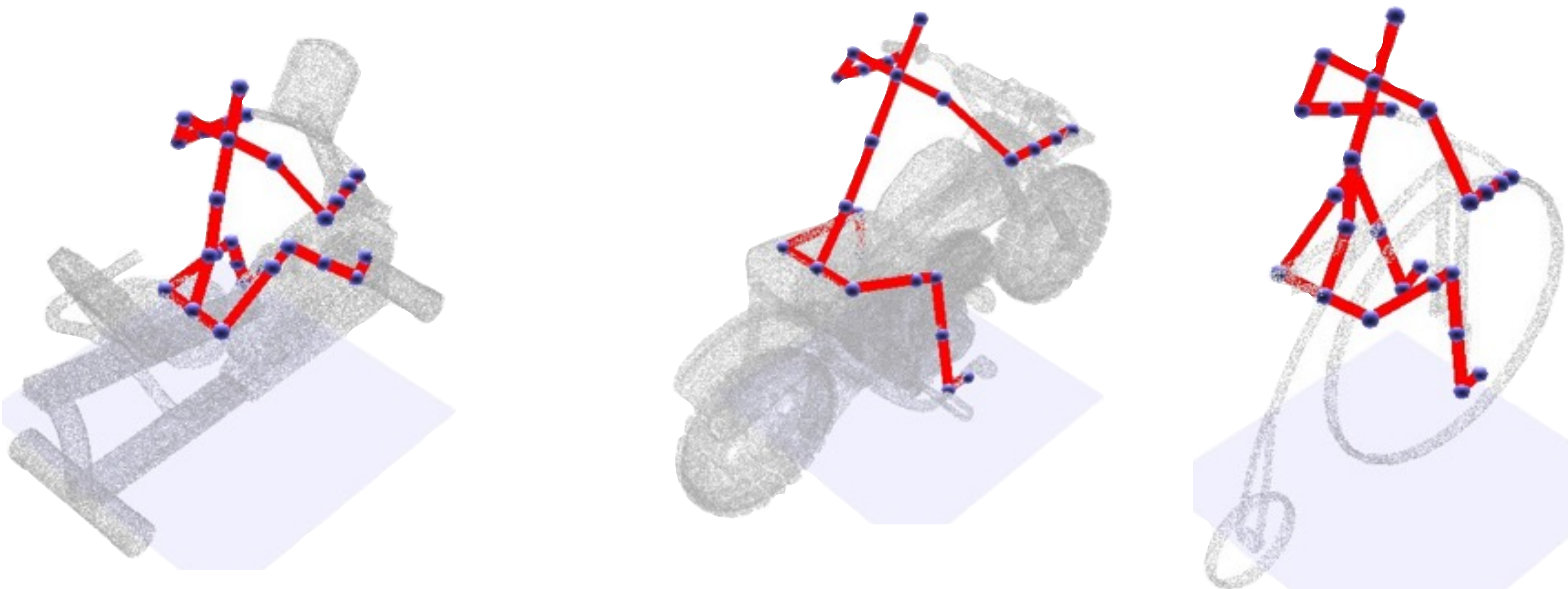
- Understand function
- Consider physical materials that make up objects
- Model mechanics and articulations

Future Work

Beyond geometry

➡ **Understand <u>function</u>**

- Consider physical <u>materials</u> that make up objects
- Model <u>mechanics</u> and articulations



Future Work

Better structural models

- Geometry processing layers in deep neural networks