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# Deformation-driven Shape Correspondence Via Shape Recognition

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SFU
gruvi
{graphics} ∪ {vision}

**Presenter:**
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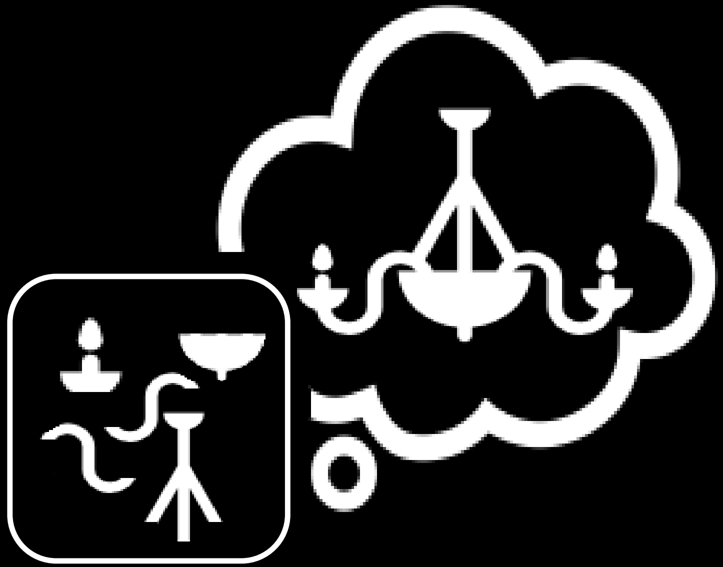
**Simon Fraser University/NUDT**

# Shape Correspondence

- Matching man-made shapes is a fundamental task for structure analysis:

**Structure Morphing**



**Structure Synthesis**

# Shape Correspondence

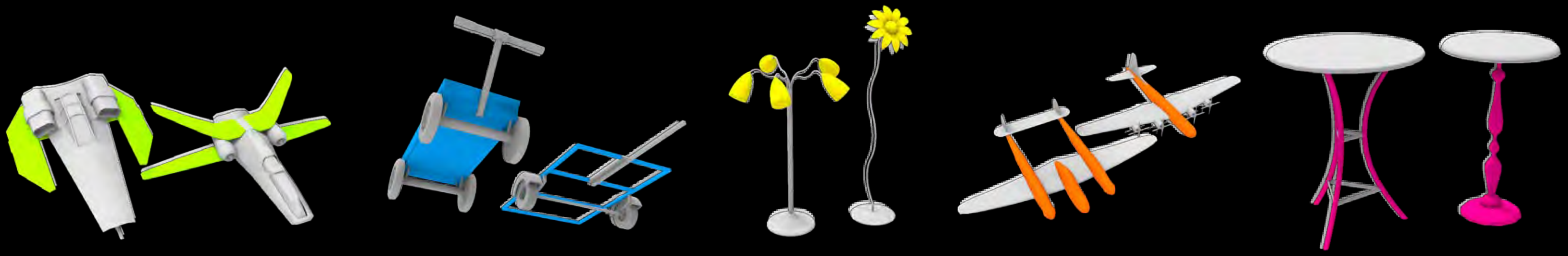
- Part-level correspondence vs. Point-level correspondence


**Part-level**


**Point-level**

# Challenge

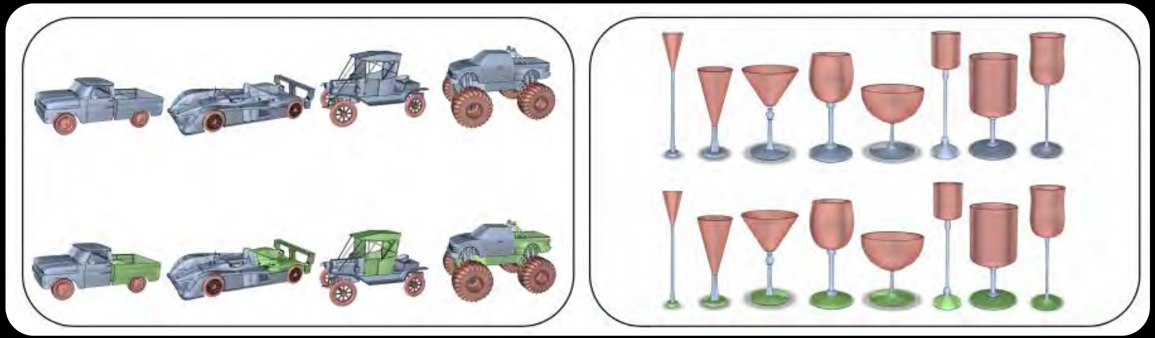
- Large variability in geometry & structure
- Inconsistent segmentation vs. fine grained matching



**Topology Variation!**

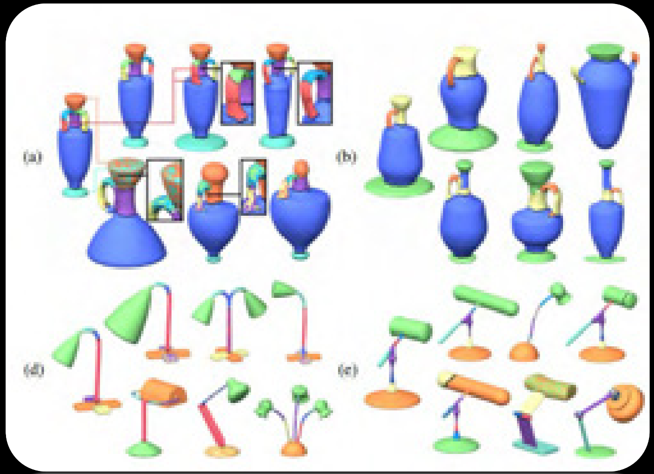
# Previous Works

- Most previous correspondence methods are based on:
  - **Part similarity**
  - **Distortion**

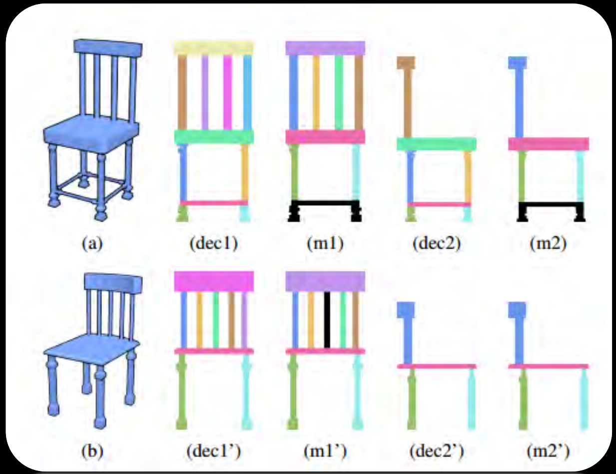


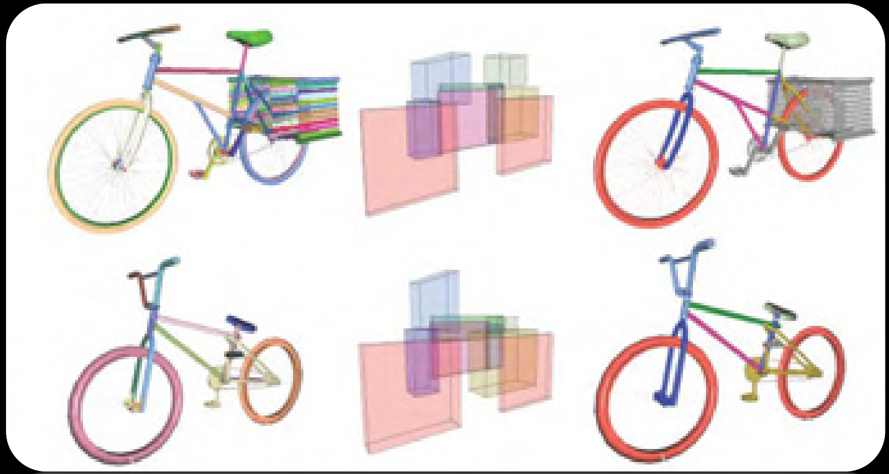
[Kaick et al. 13]

[Kleiman et al. 15]



[Fish et al. 16]

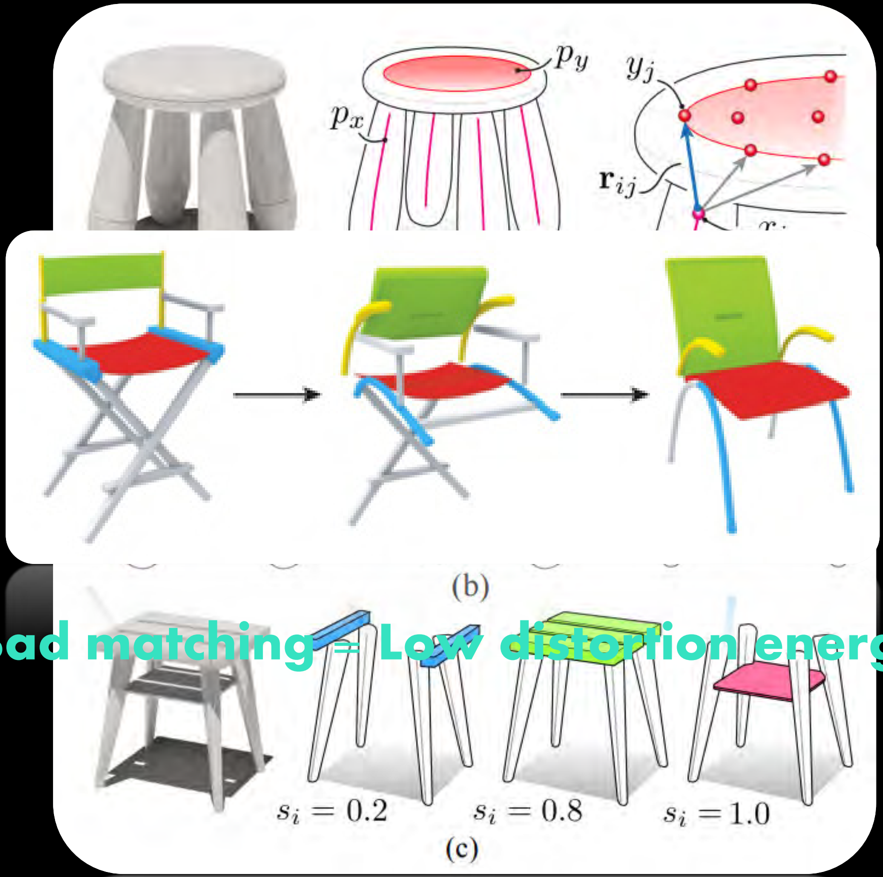


[Zheng et al. 14]

# Previous Works

- GeoTopo, our first **deformation-driven** paper
- Handle **topology variation**
- Best matching = minimal structure distortion
- **Handcrafted** deformation energy ☹

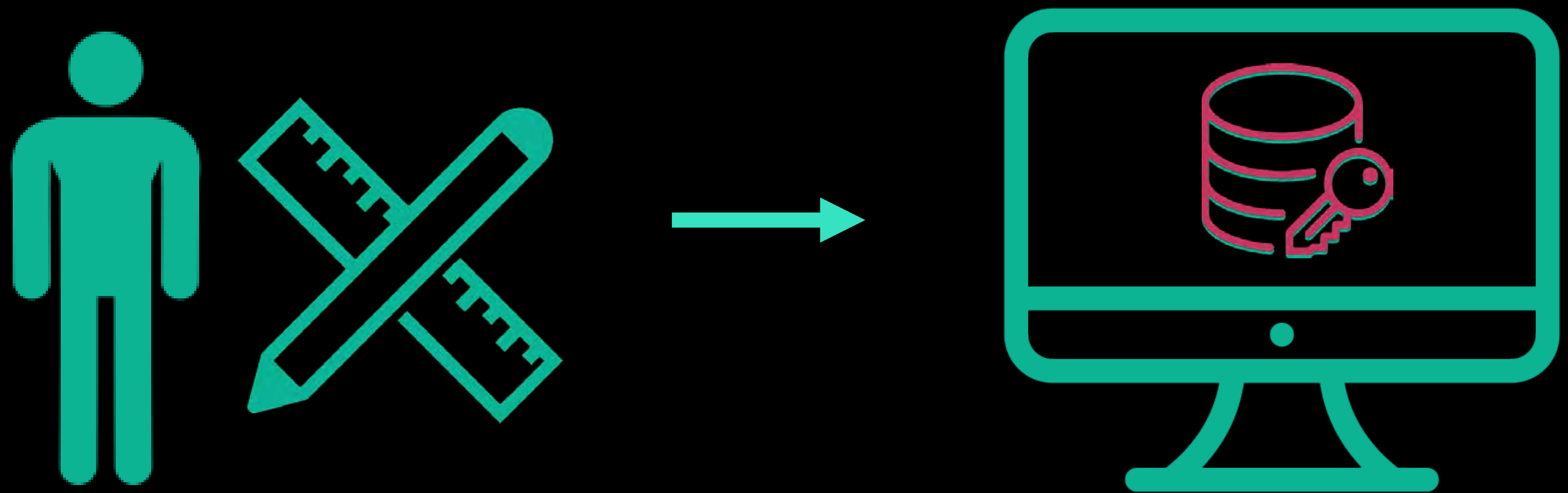



**Bad matching = Low distortion energy**

[Alhashim et al. 15]

# Data-driven Part Correspondence?

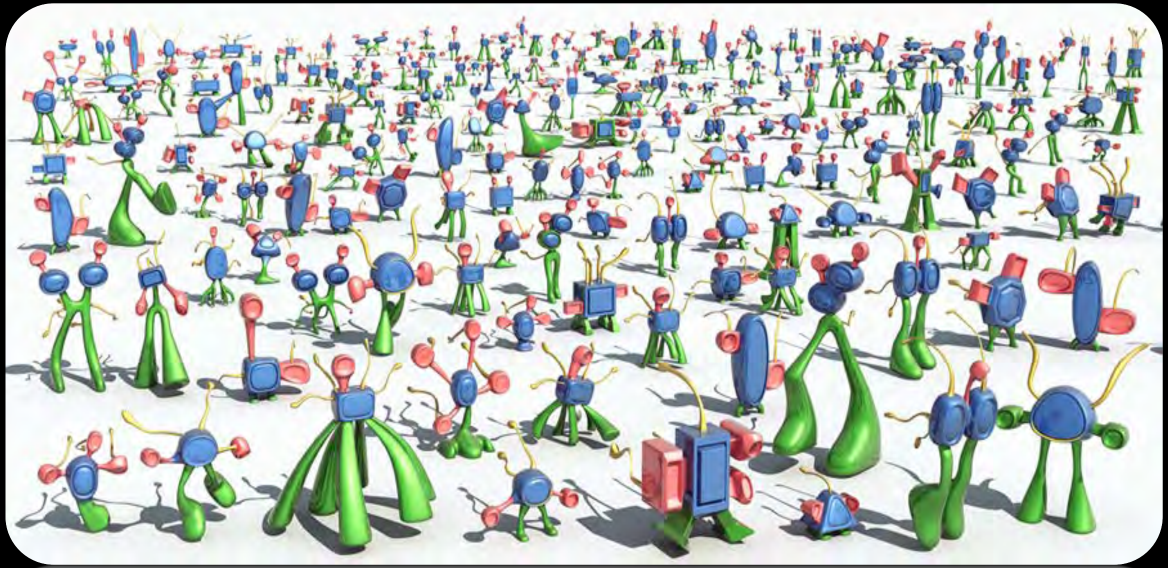
- How to define a good energy measure?



Handcrafted Energy    Data-driven Energy

# Data-driven Part Correspondence?

[COSEG Dataset 12]



Too coarse to help fine grained matching

**Existing Dataset**

**Label it ourselves**

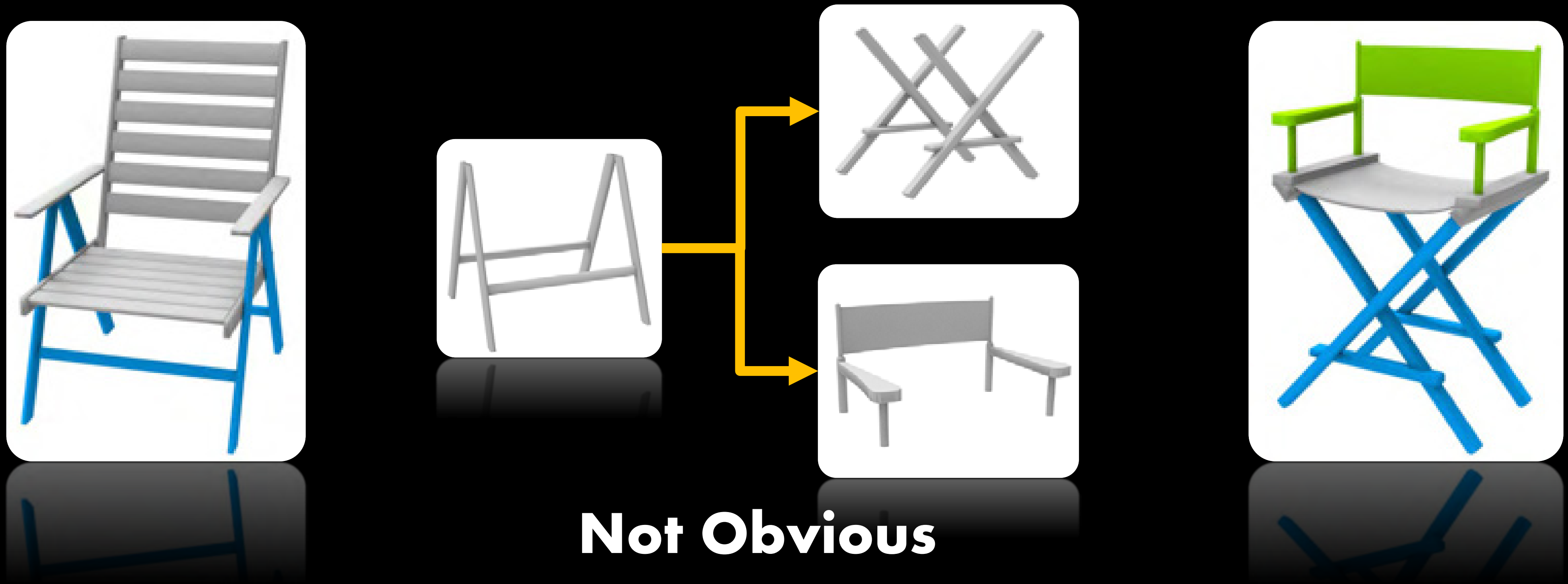
Pairwise labeling gives workload explosion

# Key Observation

- Still use deformation-driven correspondence approach
- **Data-driven** deformation energy
- Turn correspondence into a **recognition** problem
  - Training data: use **ShapeNet directly**
  - No part label needed

# Key Idea

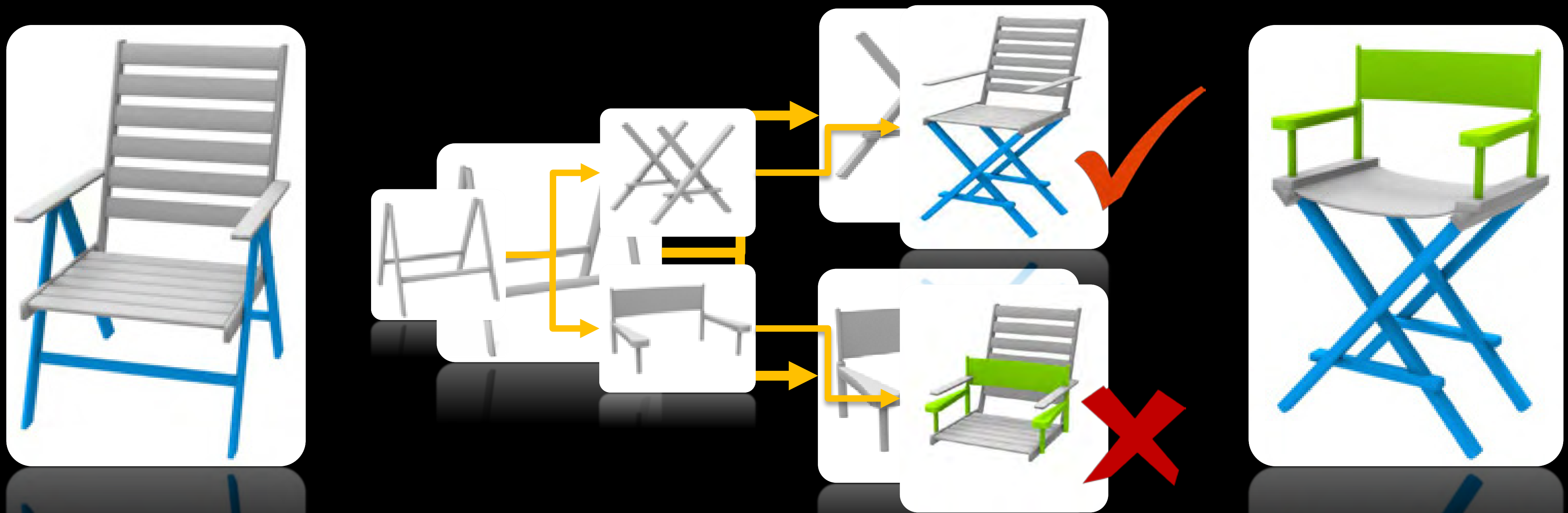
- Distortion is **HARD** to measure
- Best matching = Minimal structure distortion



**Not Obvious**

# Key Idea

- Distortion is **HARD** to measure **but recognition is not**
- Best matching = Minimal structure distortion
Most plausible

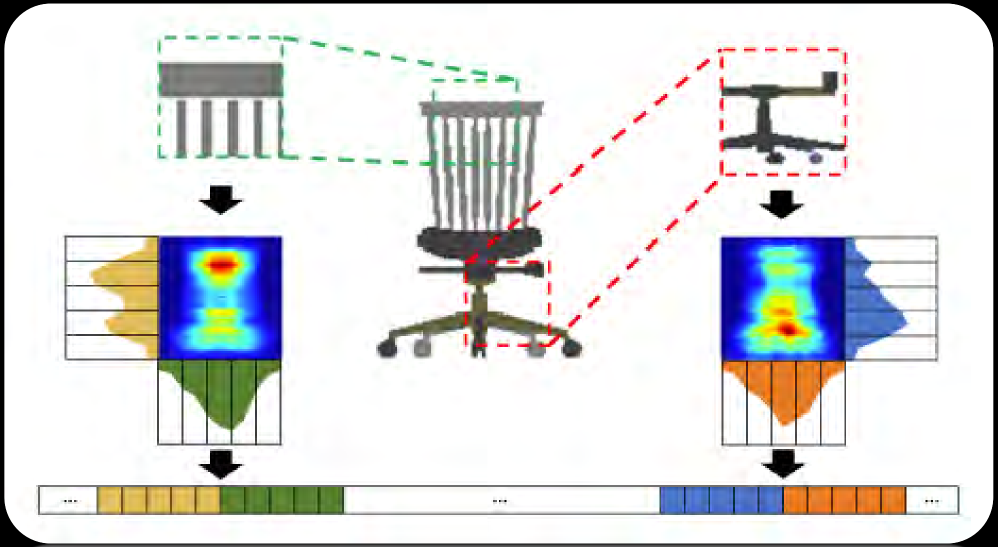


**Not Obvious**

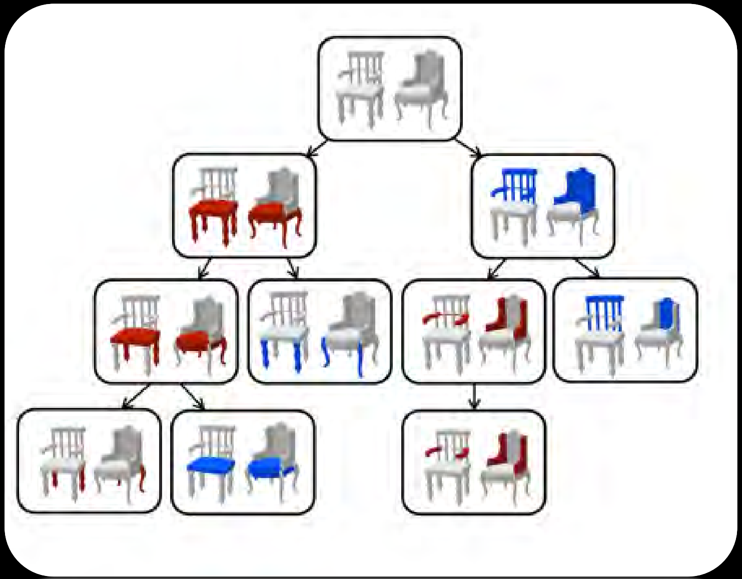
**Obvious**

# Main Contributions

- Key contribution:



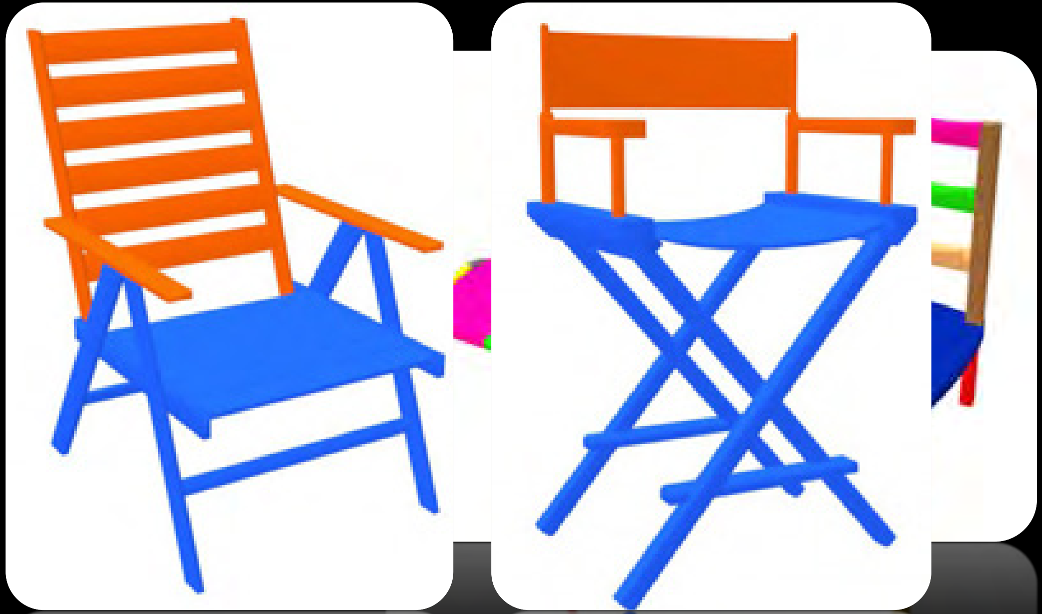
**Data-driven plausibility measure**

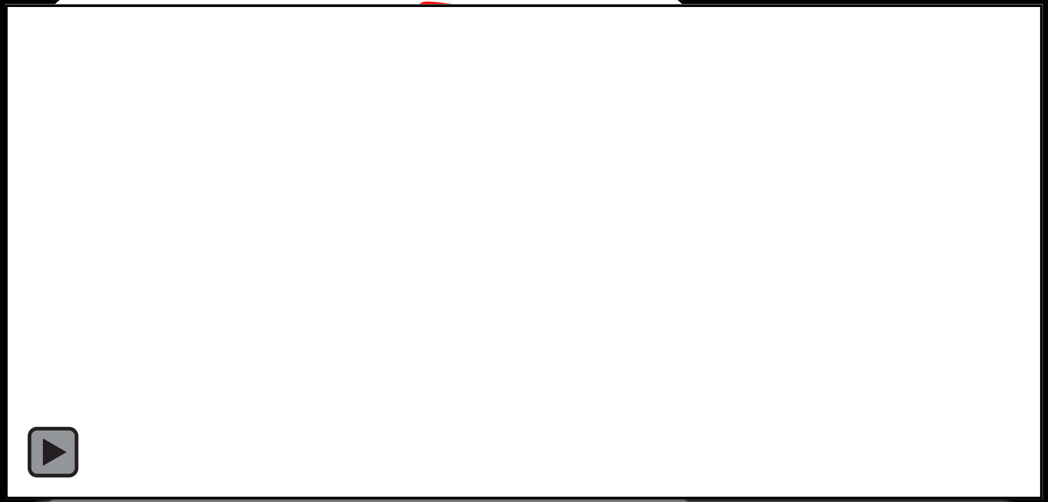


**Coarse to fine hierarchical search strategy**

# Correspondence Search

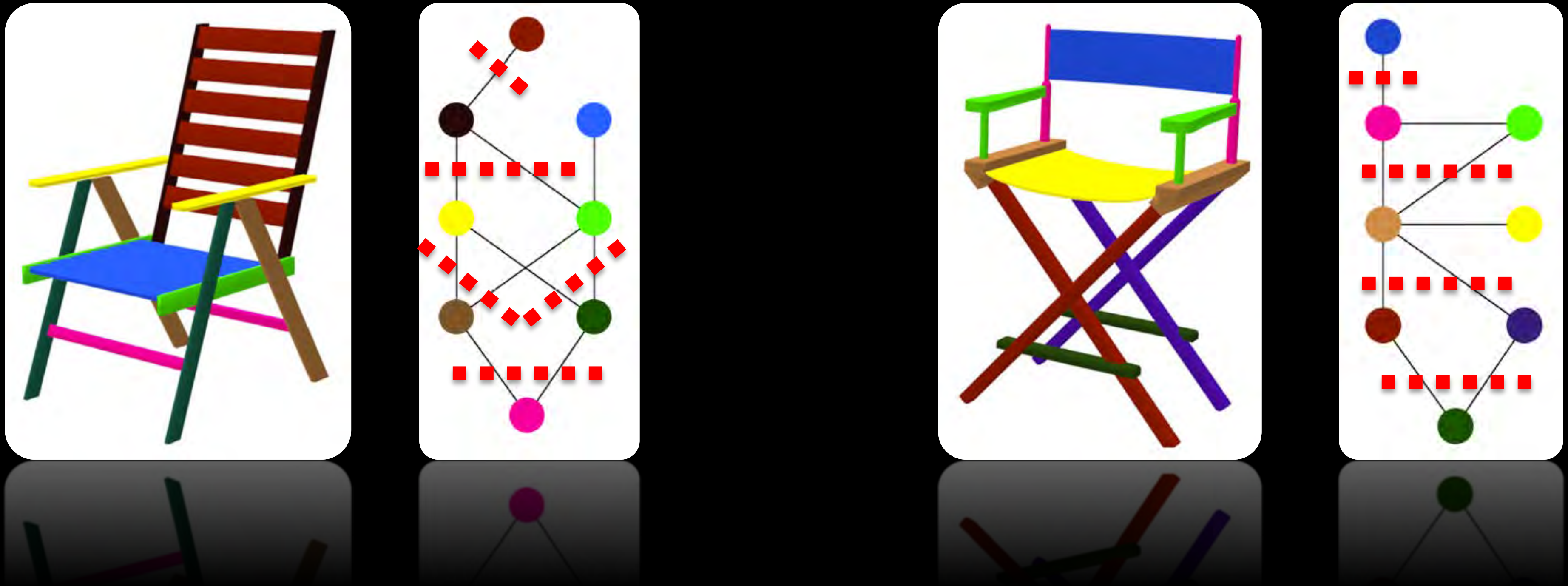
- Coarse to fine correspondence search strategy:
  - Handle inconsistent segmentation
  - More efficient





# Correspondence Search

- The correspondence search is based on binary graph partition
  - Each shape is represented as a graph G
  - Binary graph partition = Splitting G into two vertex-disjoint subgraphs



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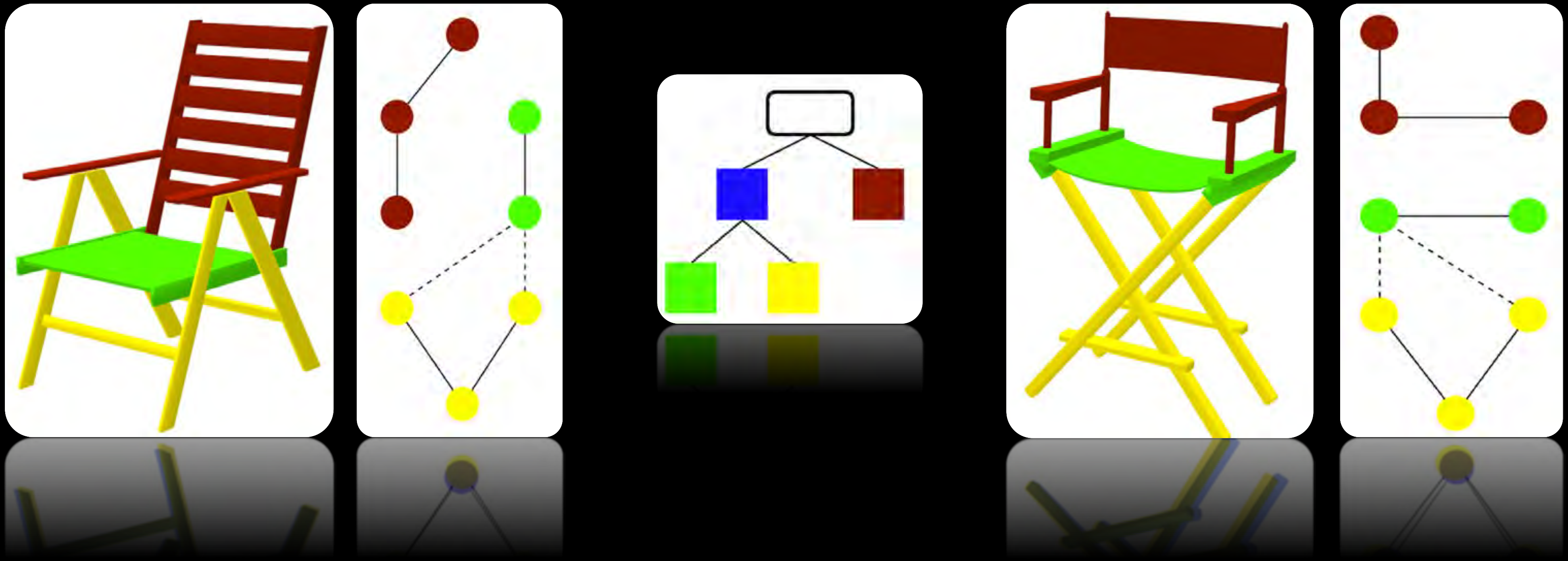
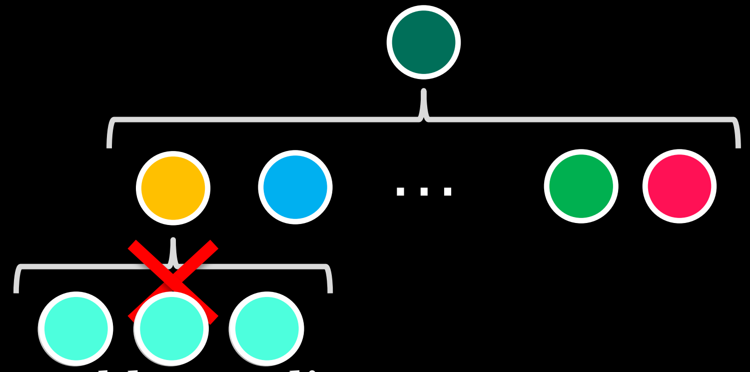


# Correspondence Search

- Three termination conditions:
  - Only one-to-one or one-to-many correspondences
  - The plausibility of all child nodes is below a threshold
  - The plausibility of all child nodes are equal within a tolerance margin



# Correspondence Search

- Replace matched parts, then propagate:
  - Connectivity recovery
  - Symmetry recovery

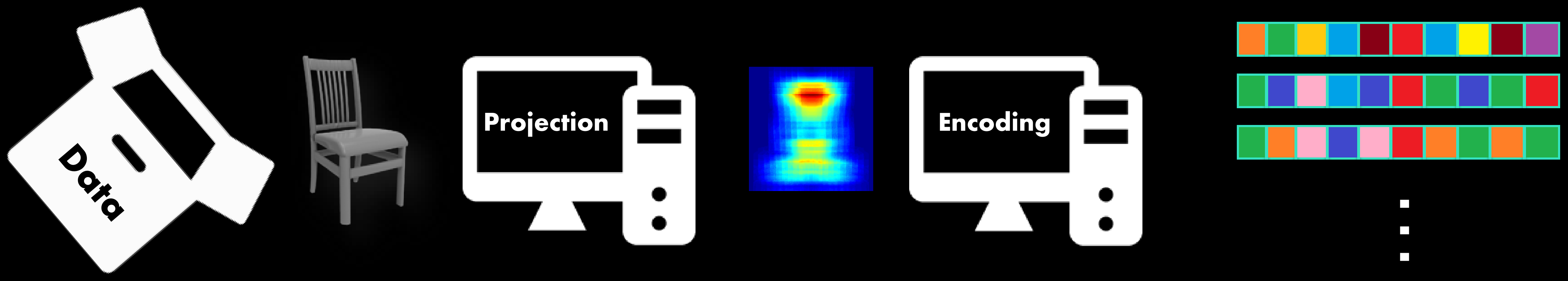
After Replacement

Connectivity Recovery

Symmetry Recovery

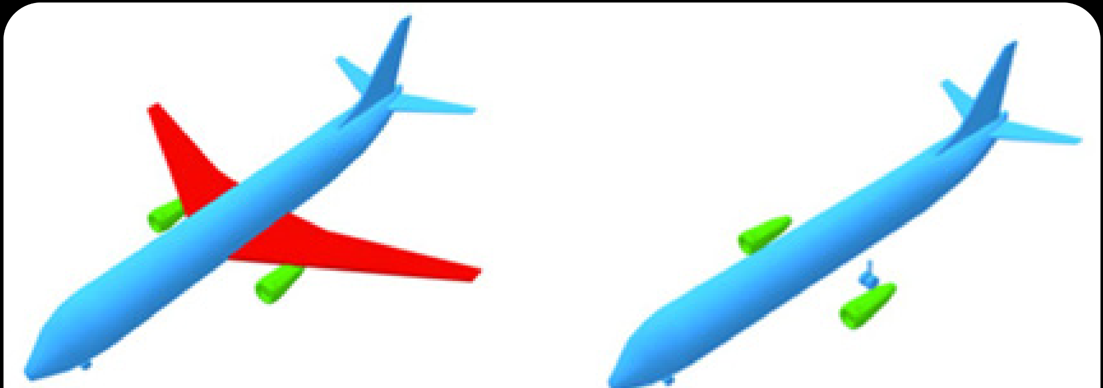
# Data-driven Plausibility Measure

- What to do:
  - Training data preparation
  - Projected image approach
  - Middle-level elements, multi-view feature encoding



# Training Data

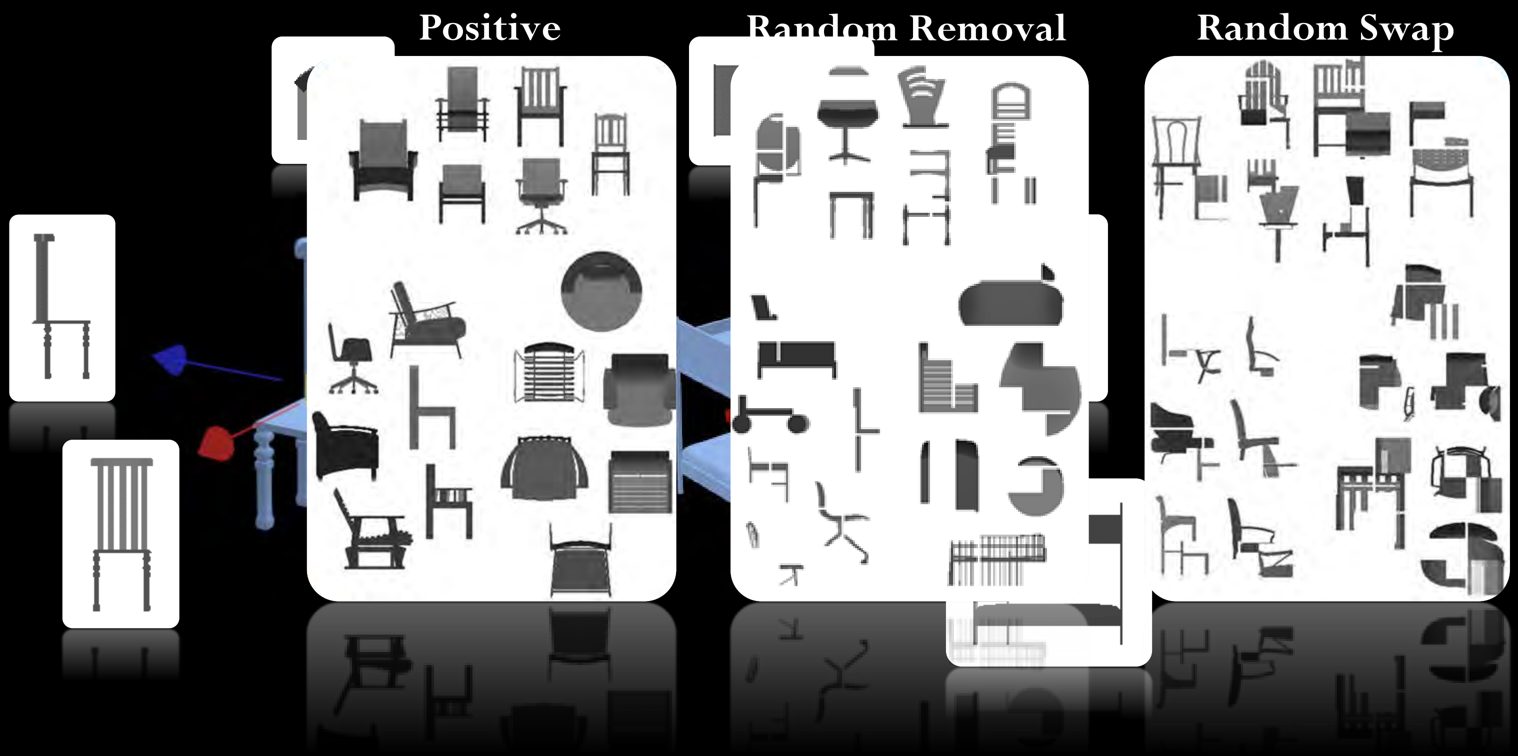
- We have a lot of positive examples already
- An in-between shape that is generated using incorrect correspondences should either:
  - lack some relevant sub-structures
  - have a messy global structure


Missing critical parts


Messy global structure

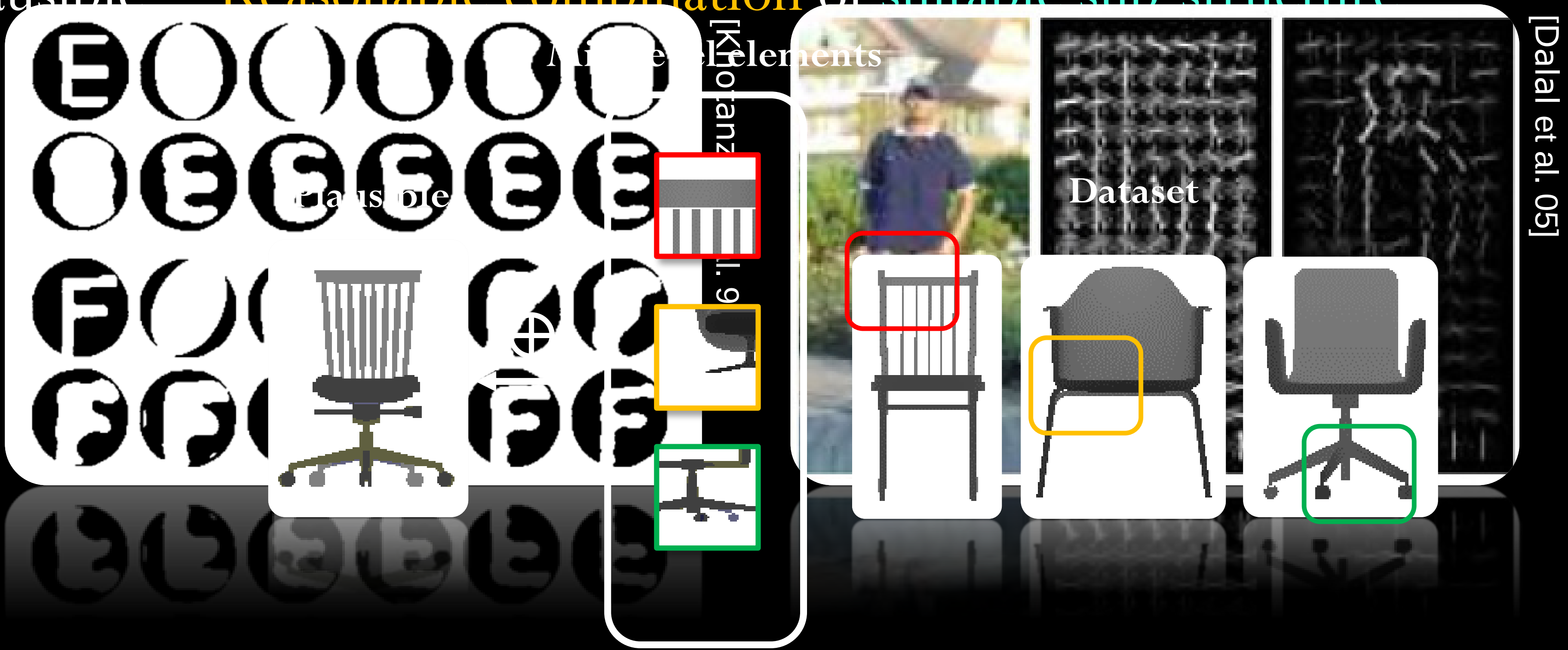
# Projected Image Approach

- An effective way to compare 3D shapes
- It is enough to use canonical views as references



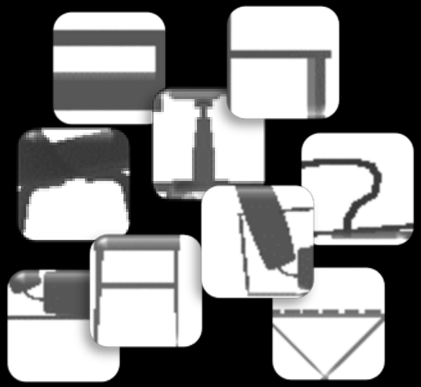
# Plausibility Evaluation

- We need a feature which can not be too global or too local
- Middle-level elements(sub-structure) based feature
- Plausible = Reasonable combination of suitable sub-structure

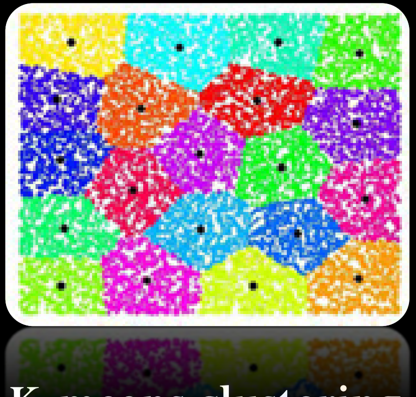


# Plausibility Evaluation

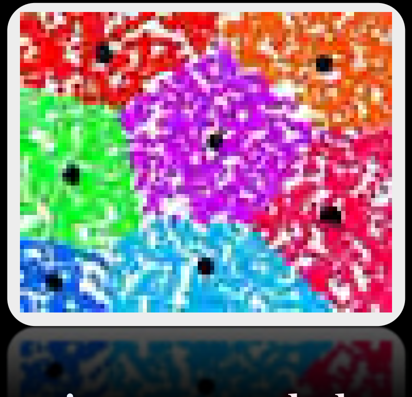
- Good middle-level elements:
  - **neither too unique, to capture relevant structures of 3D shapes**
  - **nor too common, aiming to remain flexible**
- Most representative ones



Samples
More than 50k



K-means clustering
¼ samples



Self-tuning spectral clustering
Less than 500

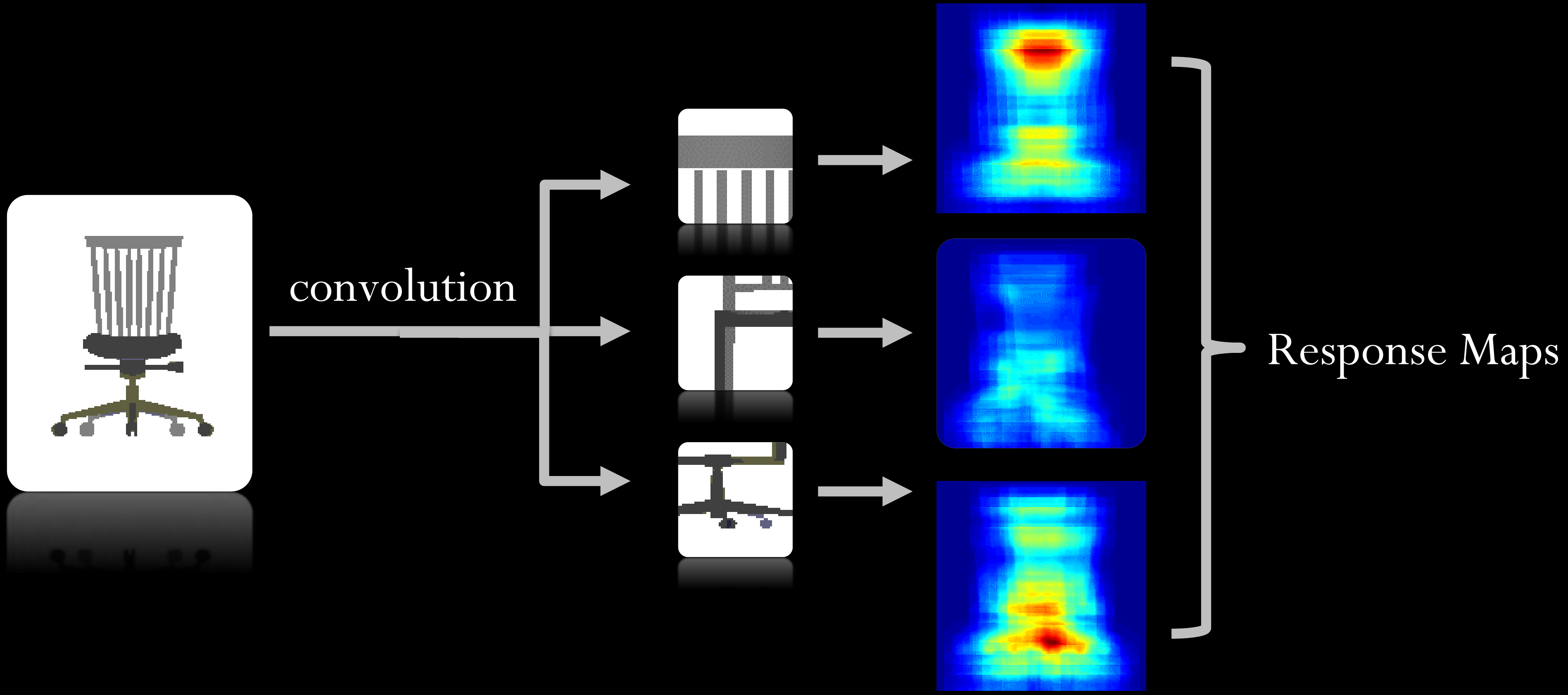
Term Frequency(TF)
Document Frequency(DF)

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

IF-IDF sorting
Top 60

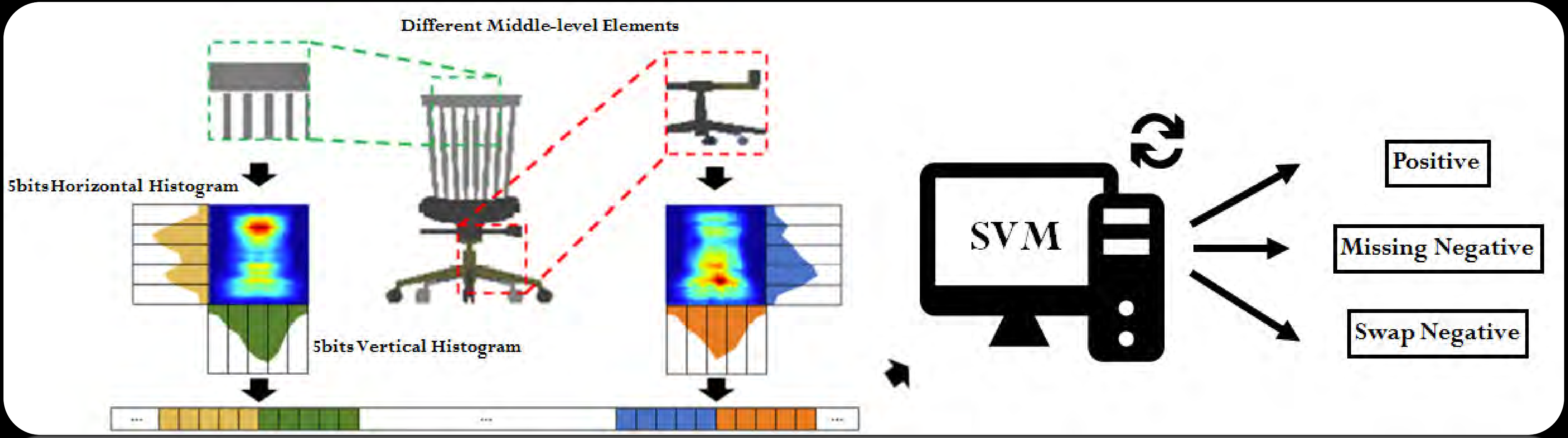
# Plausibility Evaluation

- We extend the well-known convolution operation to perform feature encoding of a given depth image

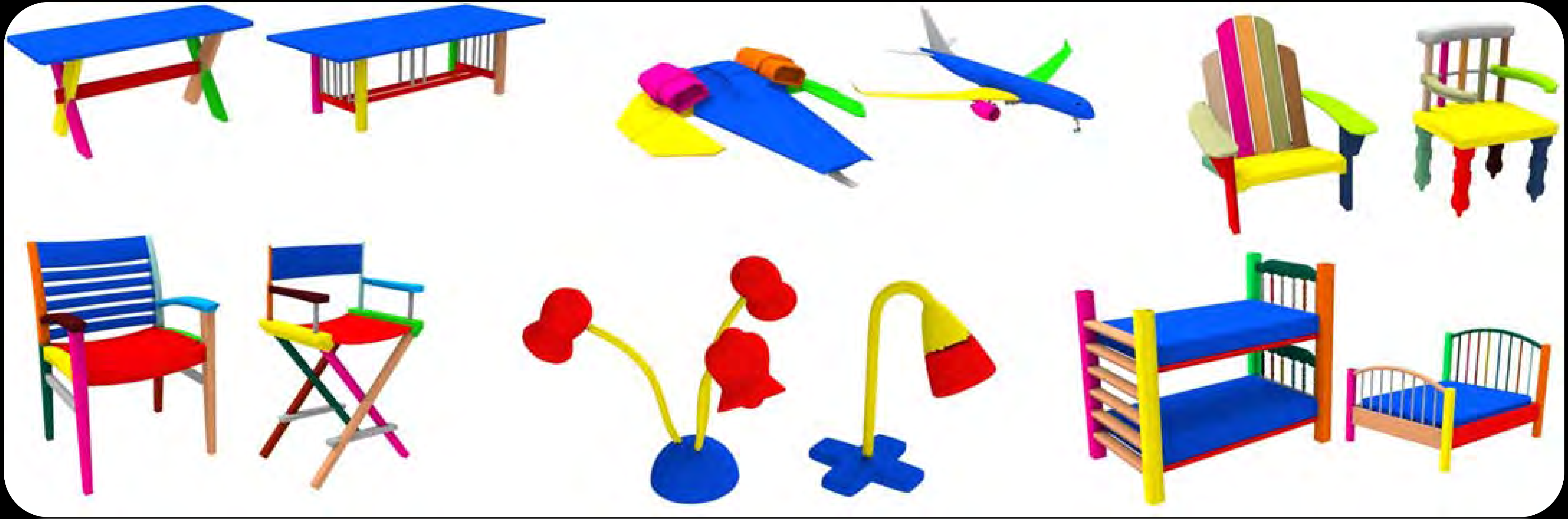


# Plausibility Evaluation

- We encode the 2D information into1D by defining 5 slices of accumulation histograms along both the horizontal and vertical directions
- A three-class SVM is trained to predict the plausibility



# Results



# Results

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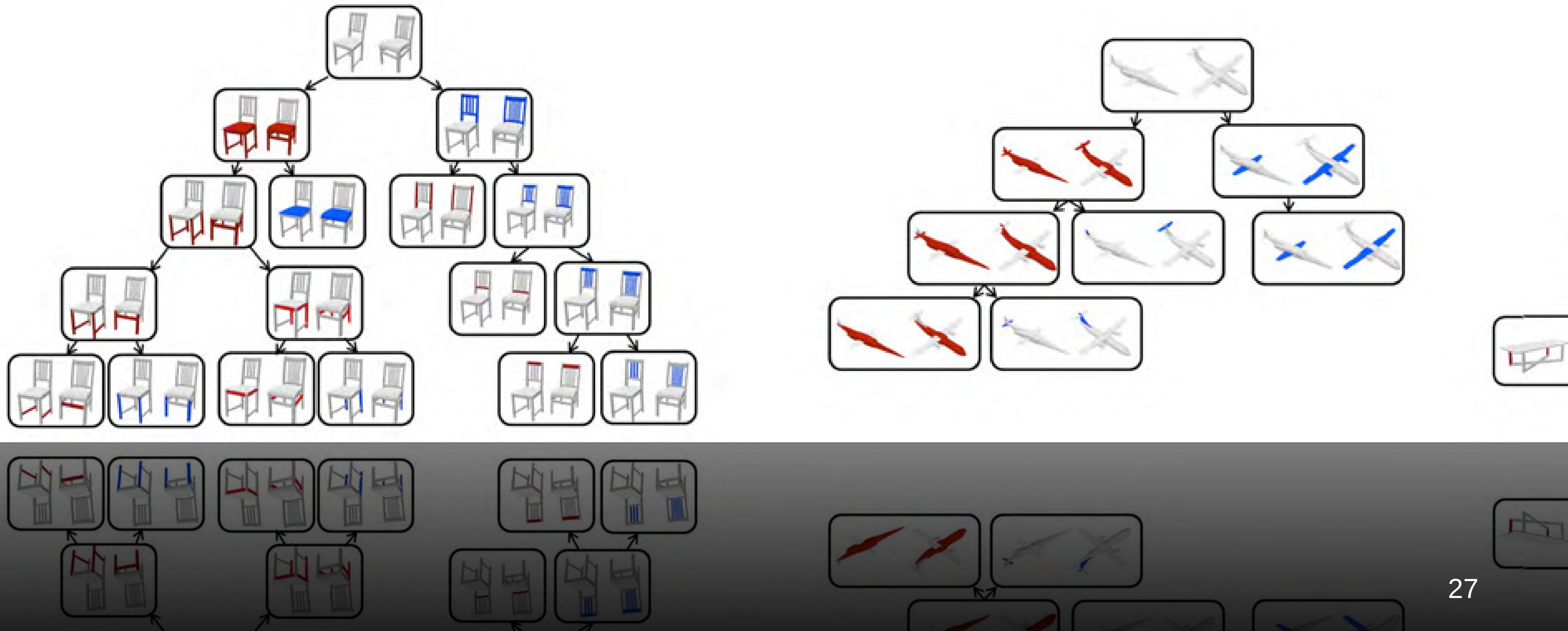
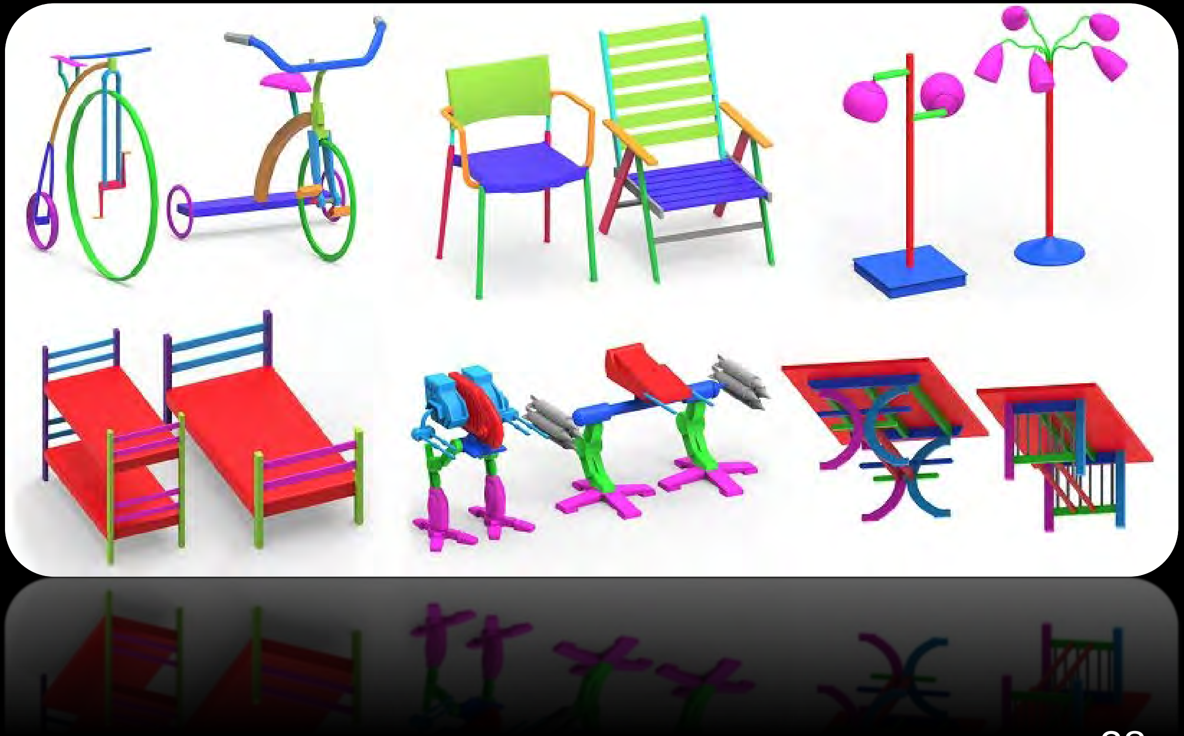


# Comparison with GeoTopo

- [GeoTopo] Deformation-Driven Topology-Varying 3D Shape Correspondence
  - Works on pairs
  - State-of-art
  - Topology variation
  - Human defined energy
  - Bottom-up search



# Evaluation

- Comparison with Geotopo

| Category | GeoTopo | | Ours | | |
|---|---|---|---|---|---|
| | Precision | Recall | Precision | Recall | $\beta$ |
| Chair | 0.69 | 0.67 | **0.83** | **0.83** | 0.2 |
| Table | 0.63 | 0.61 | **0.81** | **0.86** | 0.2 |
| Bed | 0.60 | 0.62 | **0.78** | **0.81** | 0.3 |
| Airplane | 0.60 | 0.68 | **0.80** | **0.85** | 0.25 |
| Velocipedes | **0.47** | 0.44 | 0.43 | **0.49** | 0.35 |

# Limitation

- Wrong correspondences may still generate plausible shapes
- May fail on shapes with many small parts

Shape with many small parts

Wrong match but plausible in-between

# Future Works

- Speeding up data-driven correspondence evaluation
- Partial matching
- Extending to the co-analysis setting
- Applying deep learning approach

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# Thanks

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