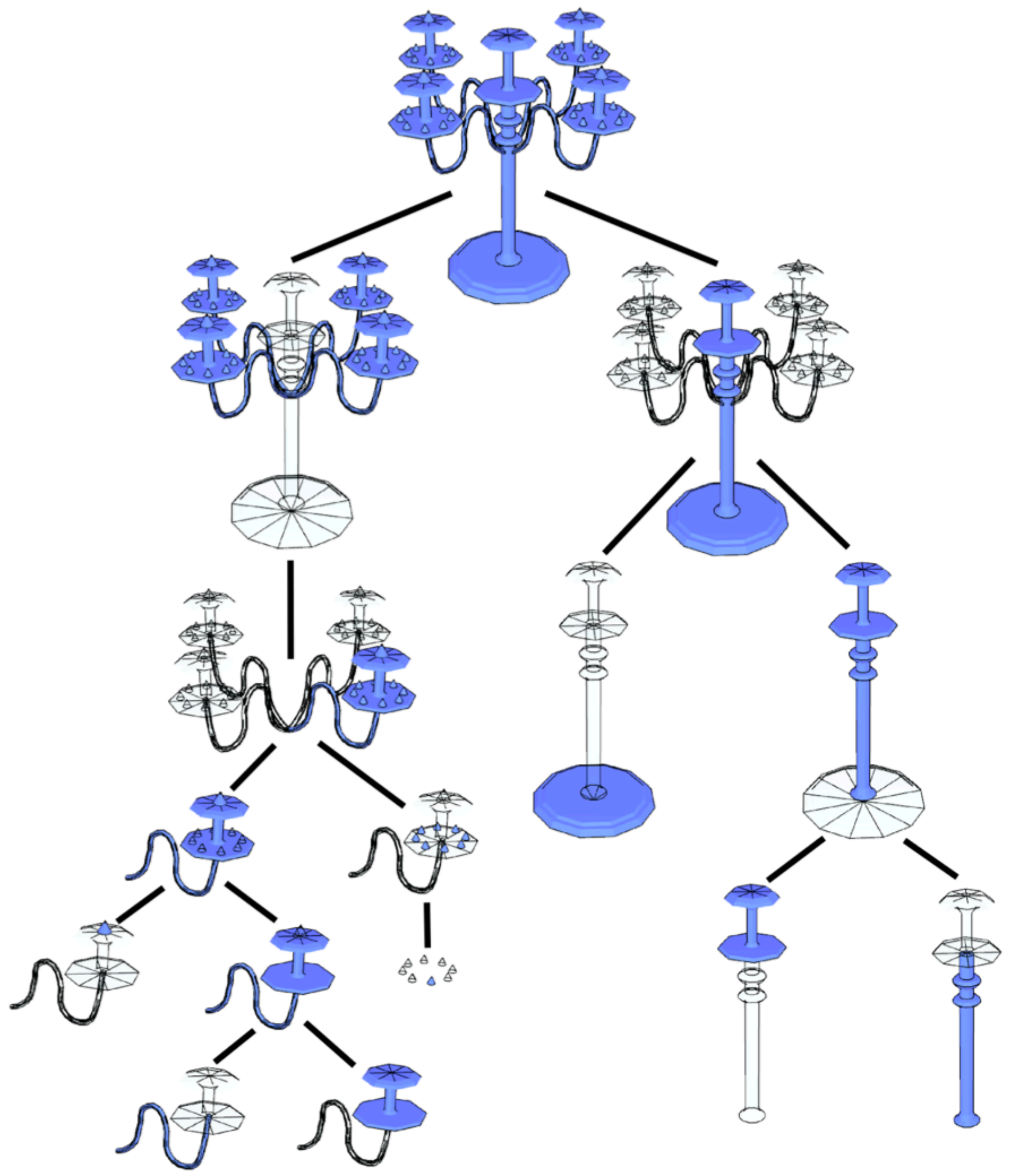
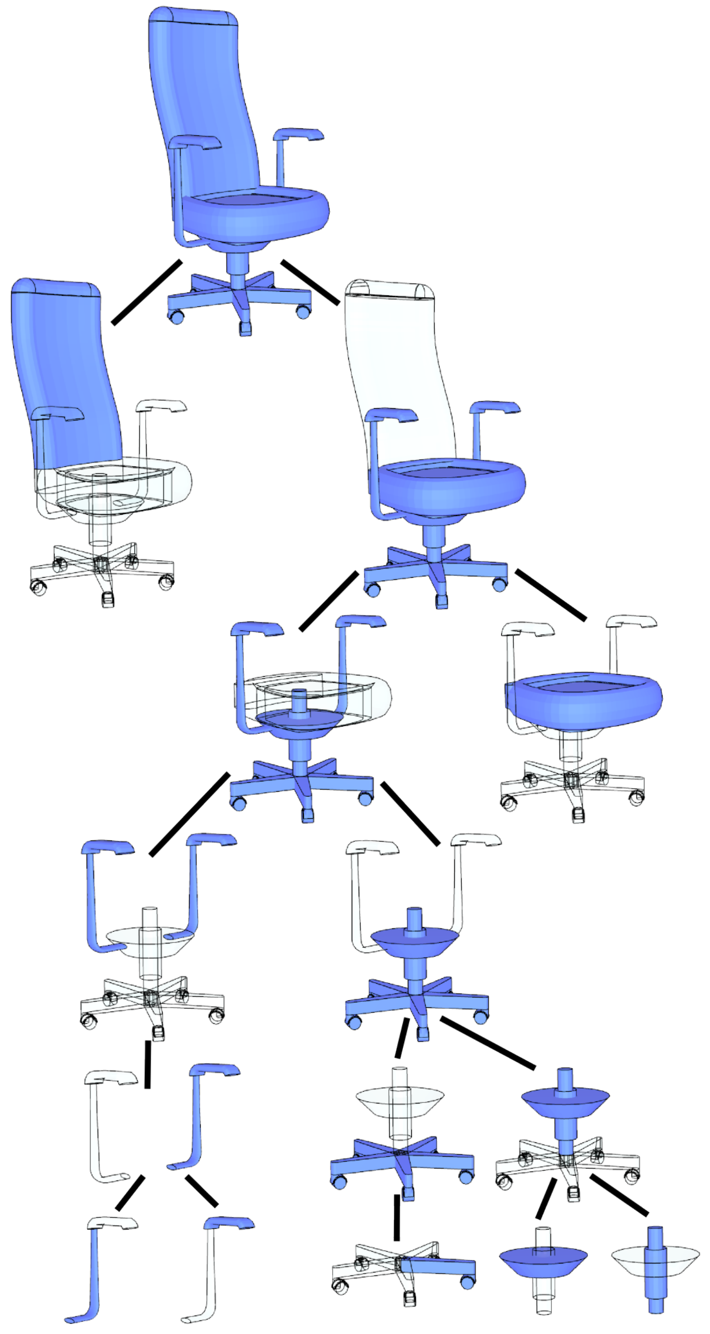
Course structure

- **Introduction to Geometric 'Structure'**
- **Extracting Structures**
  - analysis of Individual Models
  - analysis of Shape Collections (co-analysis)
  - Structural Hierarchies
- **Manipulating Structures**
  - Modeling as Structural Variations
  - Structure-guided Design
  - Organization + Exploration of Shape Collections
- **Future Directions**

Structural Hierarchies





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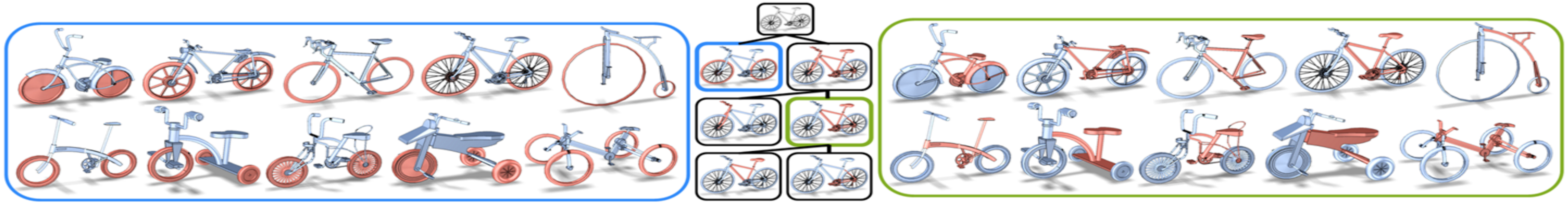
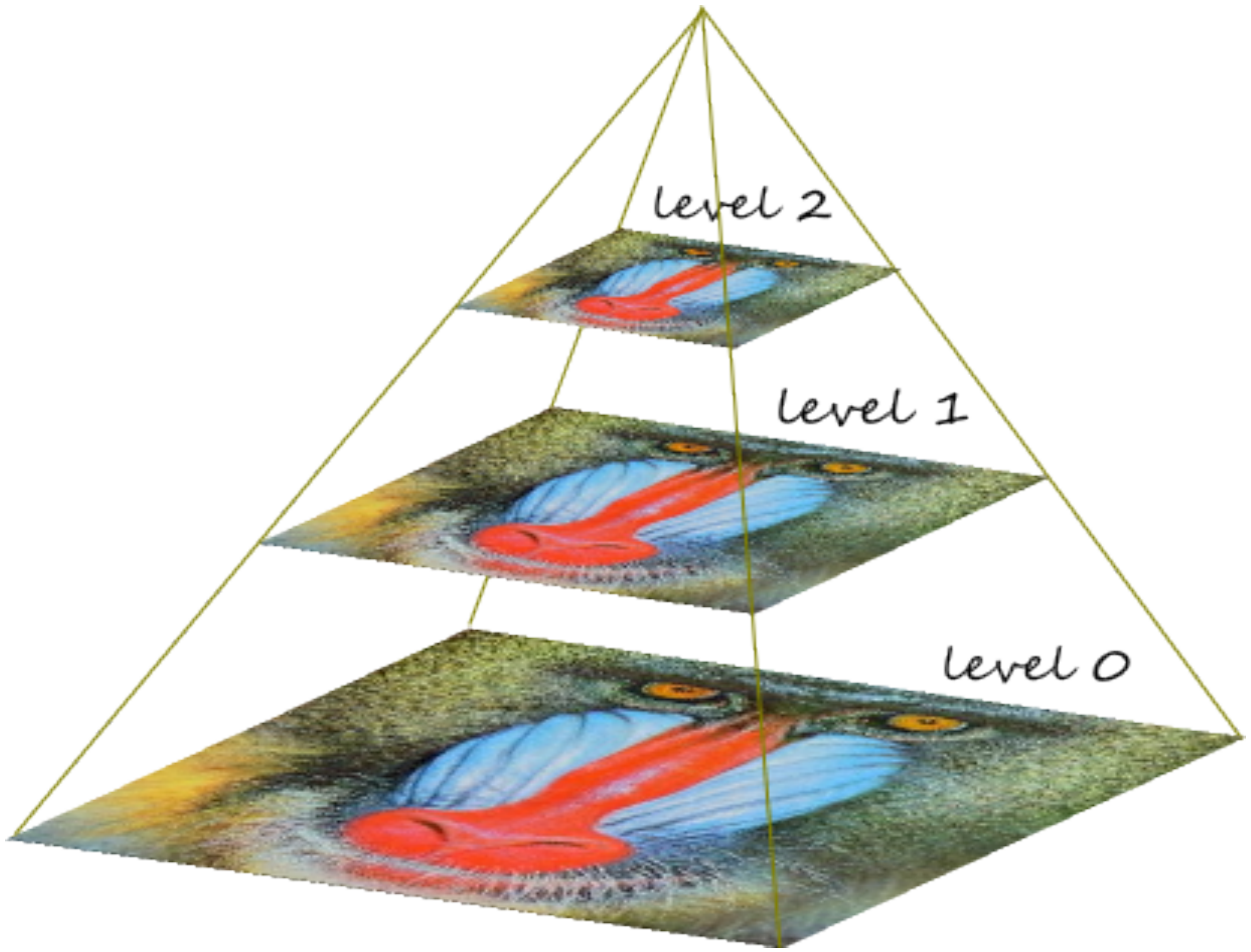
Why hierarchy?

- **Efficiency and flexibility:** hierarchy offers BOTH high-level abstraction and granularity
- **Natural choice:** human **perception** of structures IS hierarchical [Palmer 1977, Hoffman & Richards 1984]
- Appropriate model to capture **diversities in a set**: coarse levels encode commonalities; finer details lower in the tree

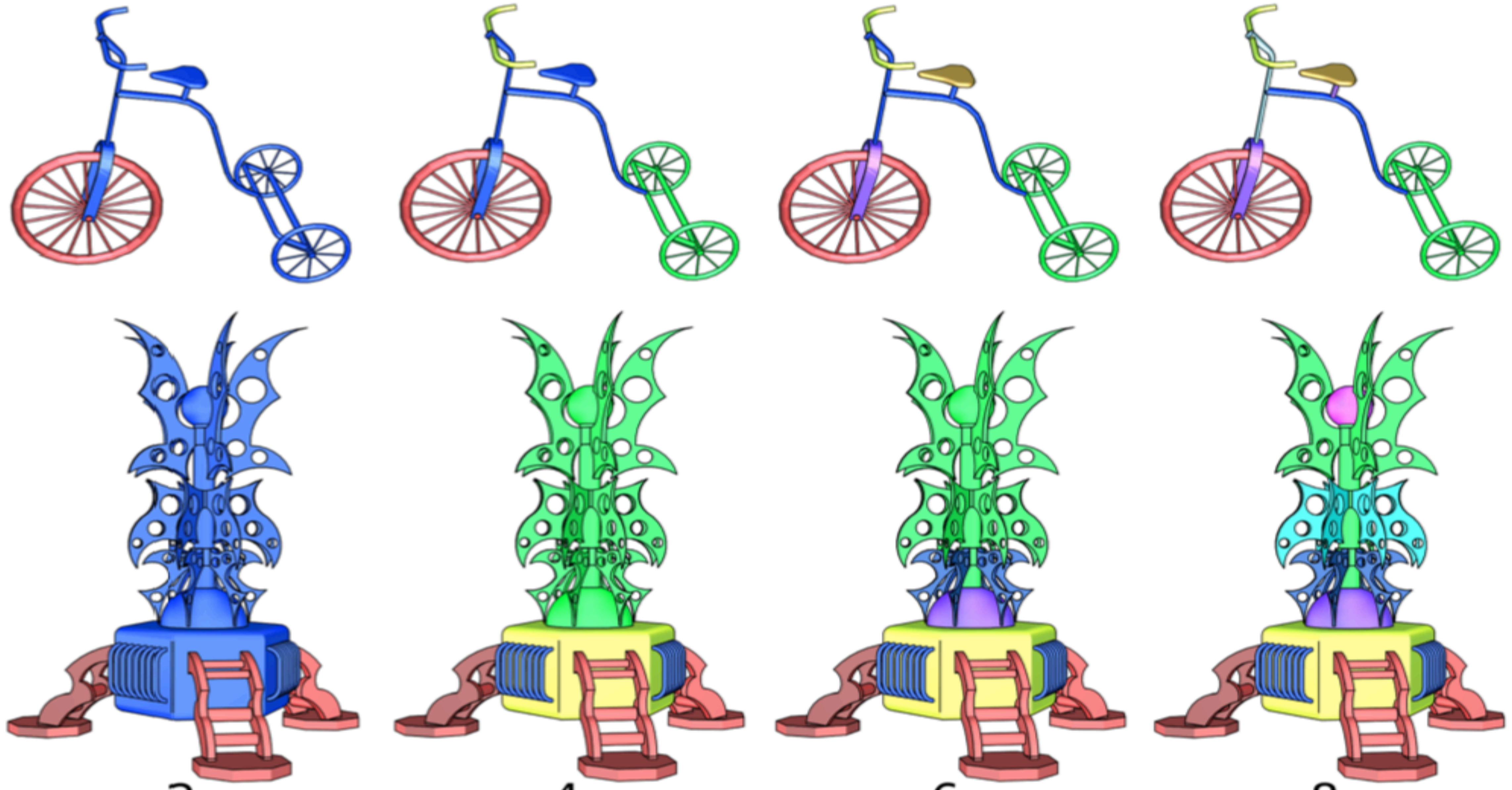


Familiar examples

- Image pyramids

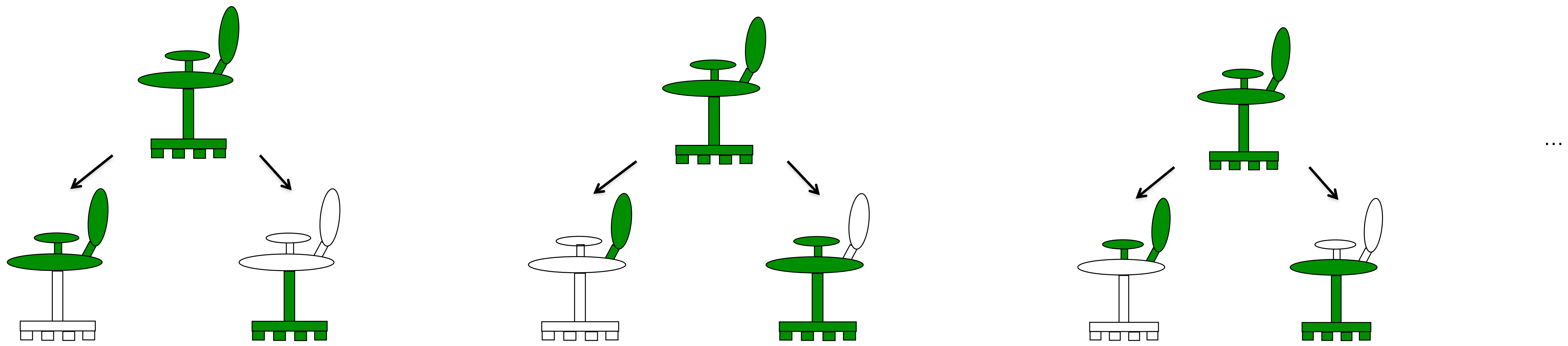


- Hierarchical segmentation



Key question

- What is **the right structural hierarchy?**
- **Challenges:**
  - Many possible hierarchies for a given shape: larger search space than (flat) shape segmentation
  - Many possible criteria for “best” structural hierarchy
  - Even human observers may disagree on what is the ground truth



We are interested in …

- … not just any structural hierarchy
- … but one that **best explains** one or a set of structures
- Exploit power of **symmetry** for analyzing individual shapes [Martinet 2007, Simari 2006, Wang 2011, Zhang 2013]
- Exploit power of a set for **co-hierarchical analysis** [van Kaick 2013]

Hierarchy construction

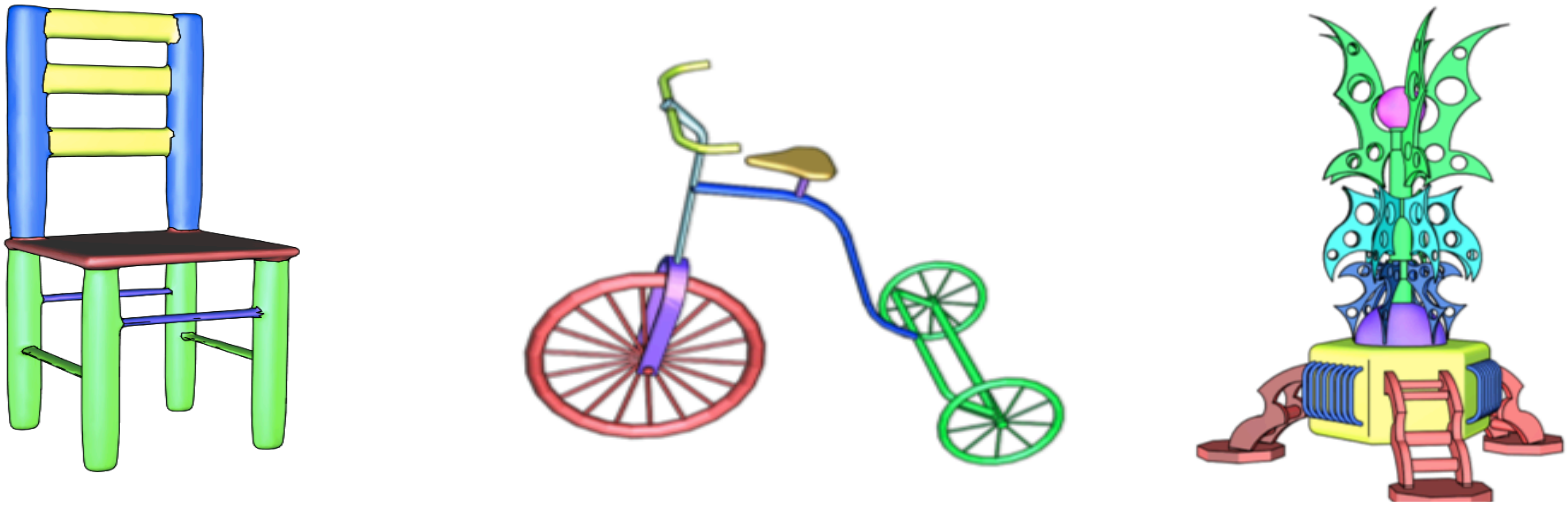
Two basic solution paradigms:

- Top-down
  - Recursively split or divide an input shape
- Bottom-up
  - Start with a fine segmentation into primitive parts
  - Then recursively group parts, e.g., via graph contraction

Key ingredient: how to prioritize the operations

Why symmetry?

- Symmetric parts tend to perform **the same function**

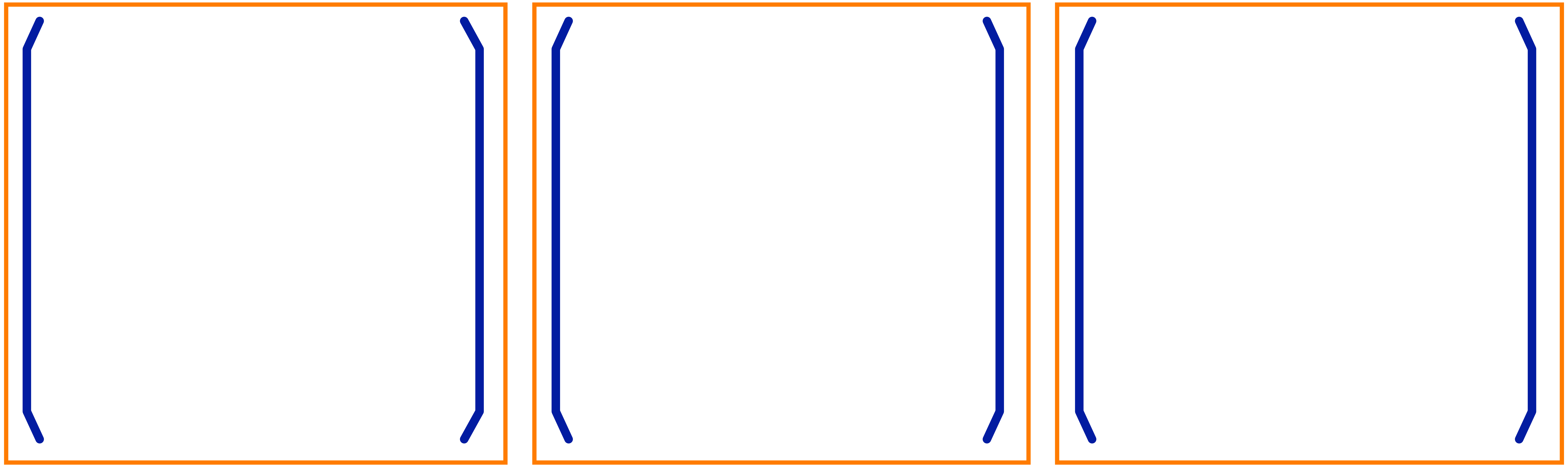


Why symmetry?

- Symmetry leads to **“better explanation”** of structures
  - With symmetry comes **redundancy**
  - Removing redundancy leads to more **compact** representations
  - A compact representation tends to be the right representation
  - Occam’s Razor: other things being equal, the **simplest**, which is likely the most compact, explanation tends to be the **best explanation**
  - Works on **minimum description length (MDL)** follows this line of thought

Why symmetry?

- Perceptual grouping via Gestalt law of symmetry



Semantics

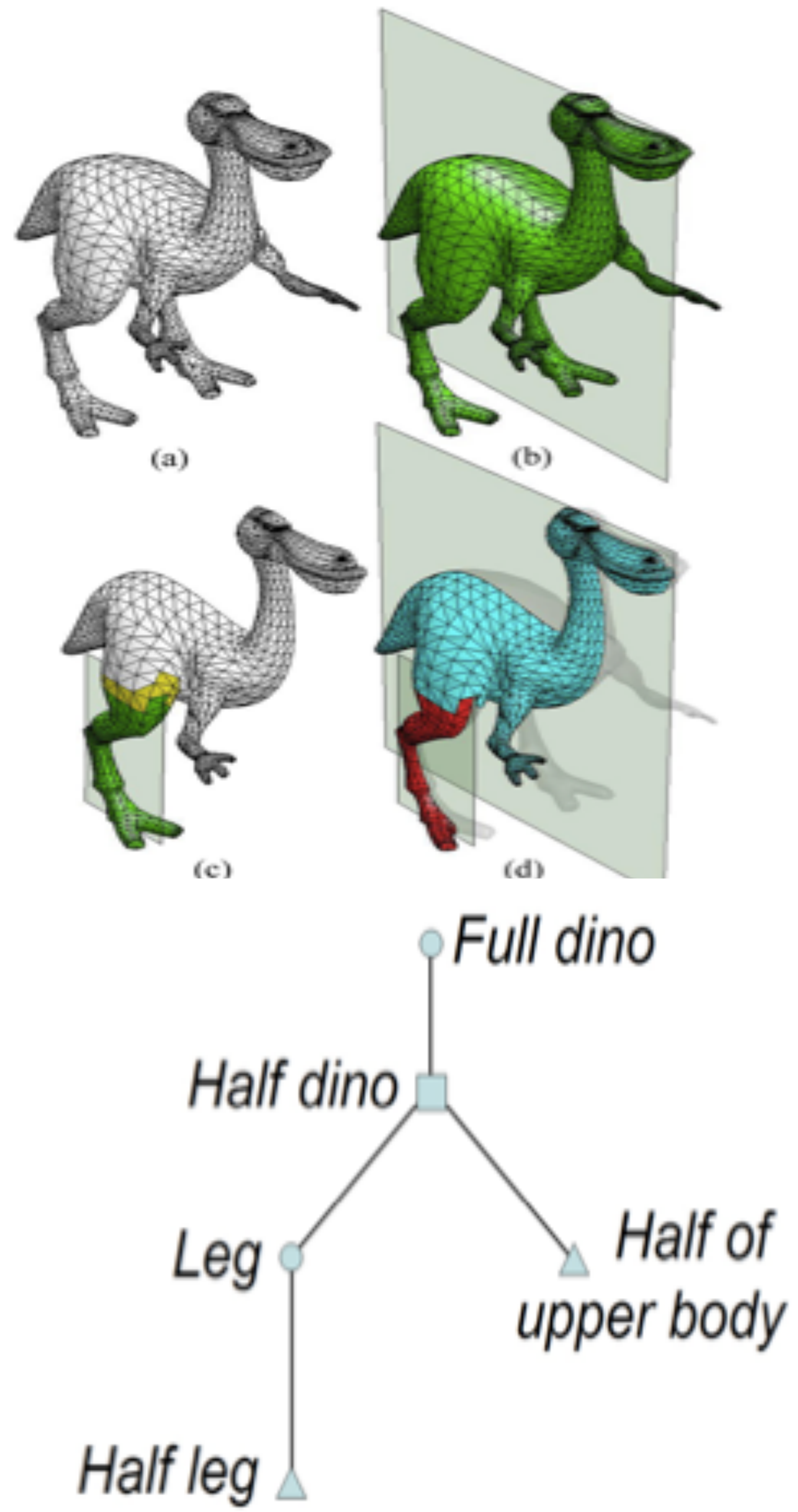
- Symmetry enables shape analysis at a **semantic** level:
  - Role in functional grouping
  - Role in offering the simplest (best) explanation
  - Role in perceptual grouping
- However, symmetry is
  - a purely **geometric** notion: explicit detection **w/o training data**
  - but requires more **global** analysis

Folding meshes [Simari et al. 2006]

Key idea: "fold" reflection symmetries for compact shape representation

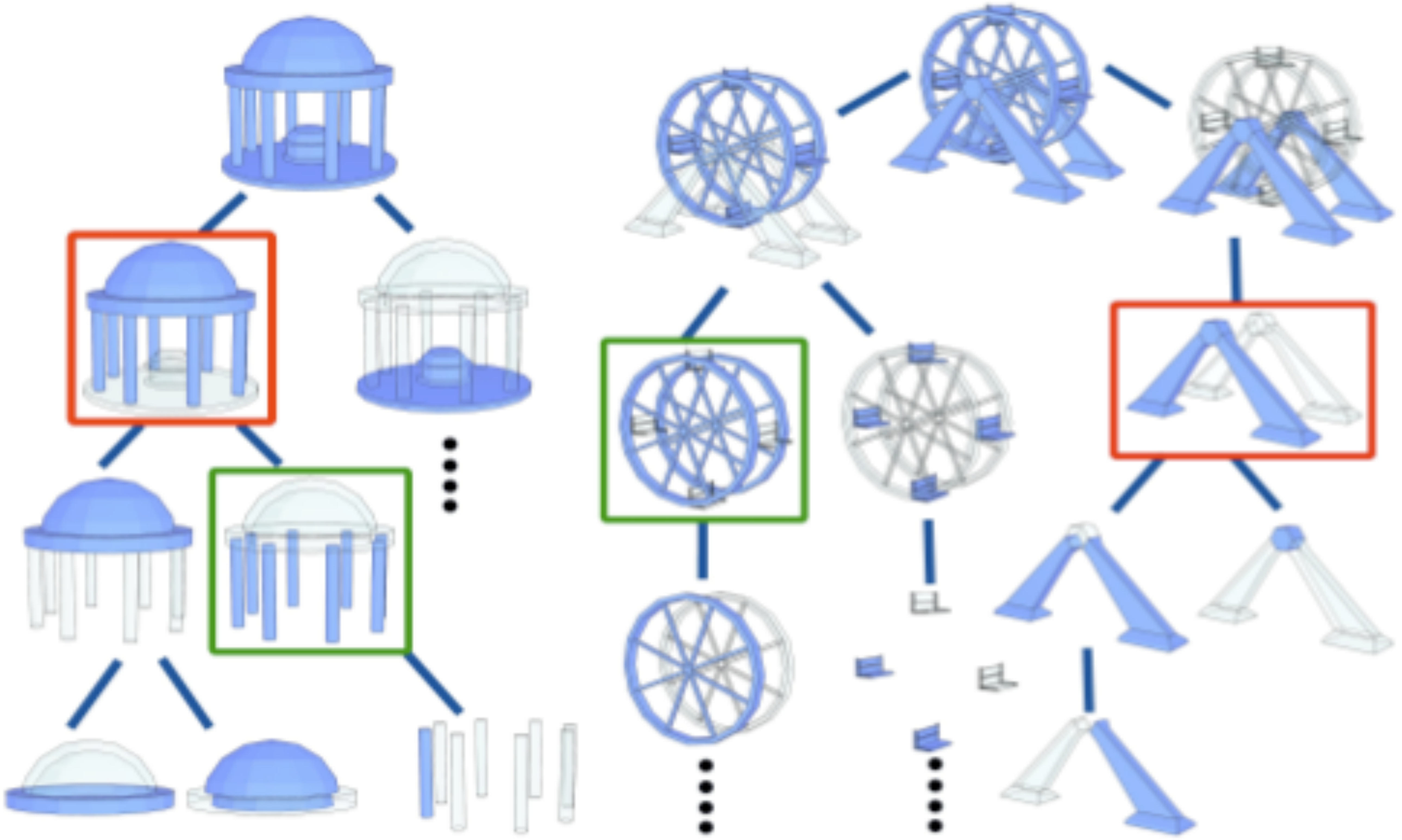
- Detect major reflection symmetry
- Divide shape into symmetric part *A* (full dinosaur) and the rest *B*
- Recursively process *B* and half of *A*

• Top-down: folding mesh hierarchy



Symmetry hierarchy [Wang et al. 2011]

Key idea: symmetry guides **grouping and assembly** of shape parts for a meaningful hierarchical part organization.

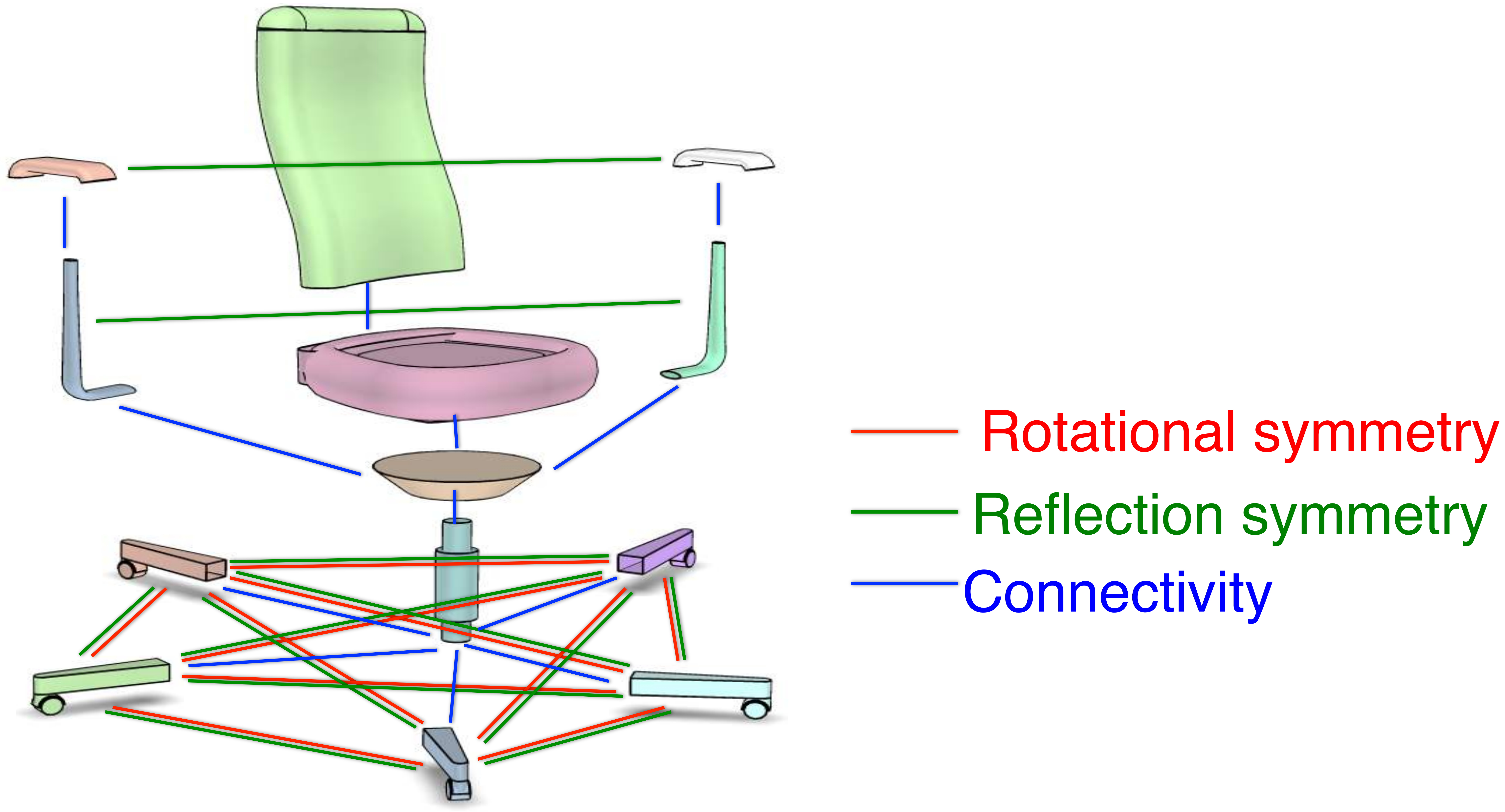


Hierarchy construction

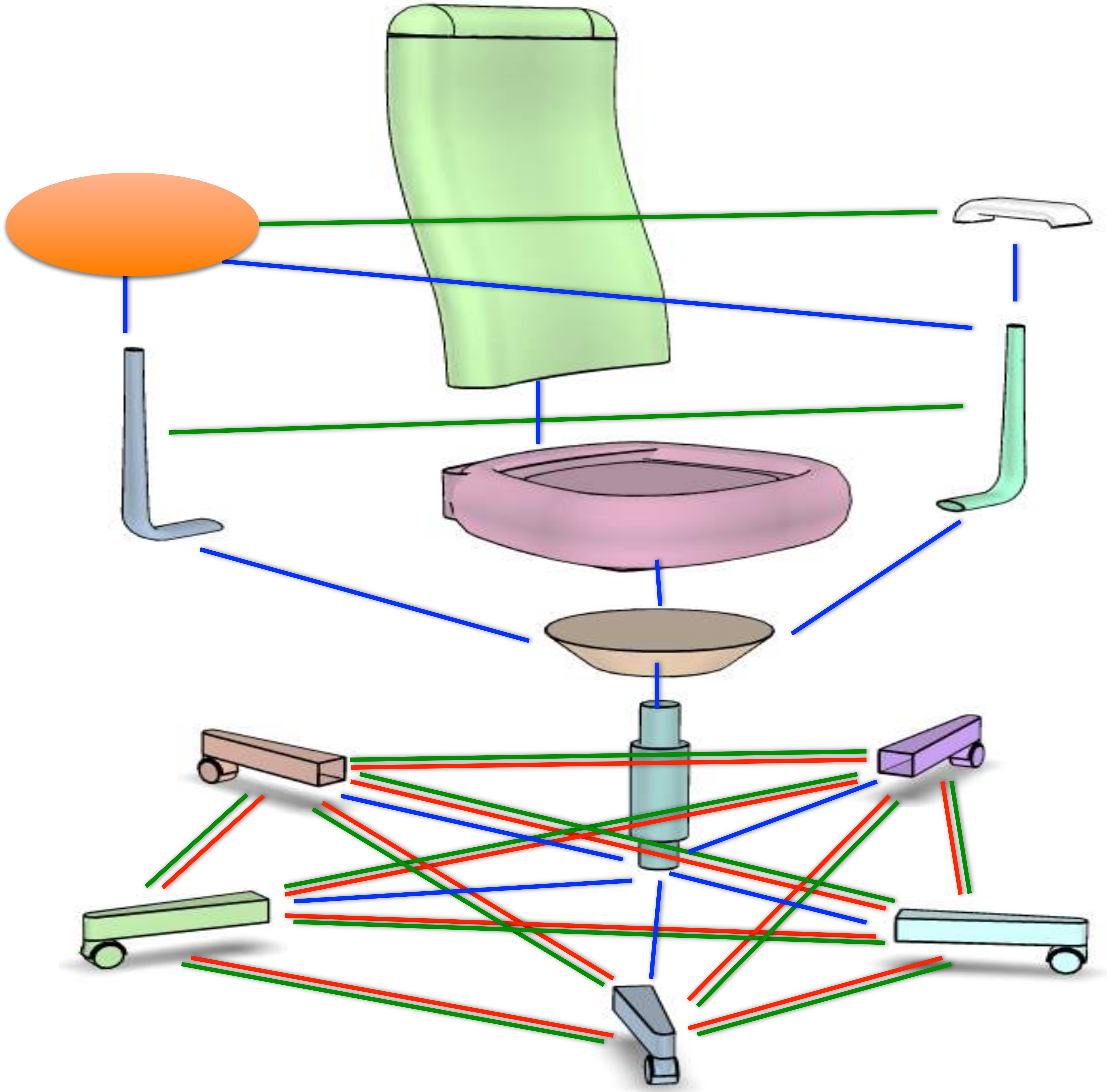
Pre-segmentation

Symmetry detection

Initial graph



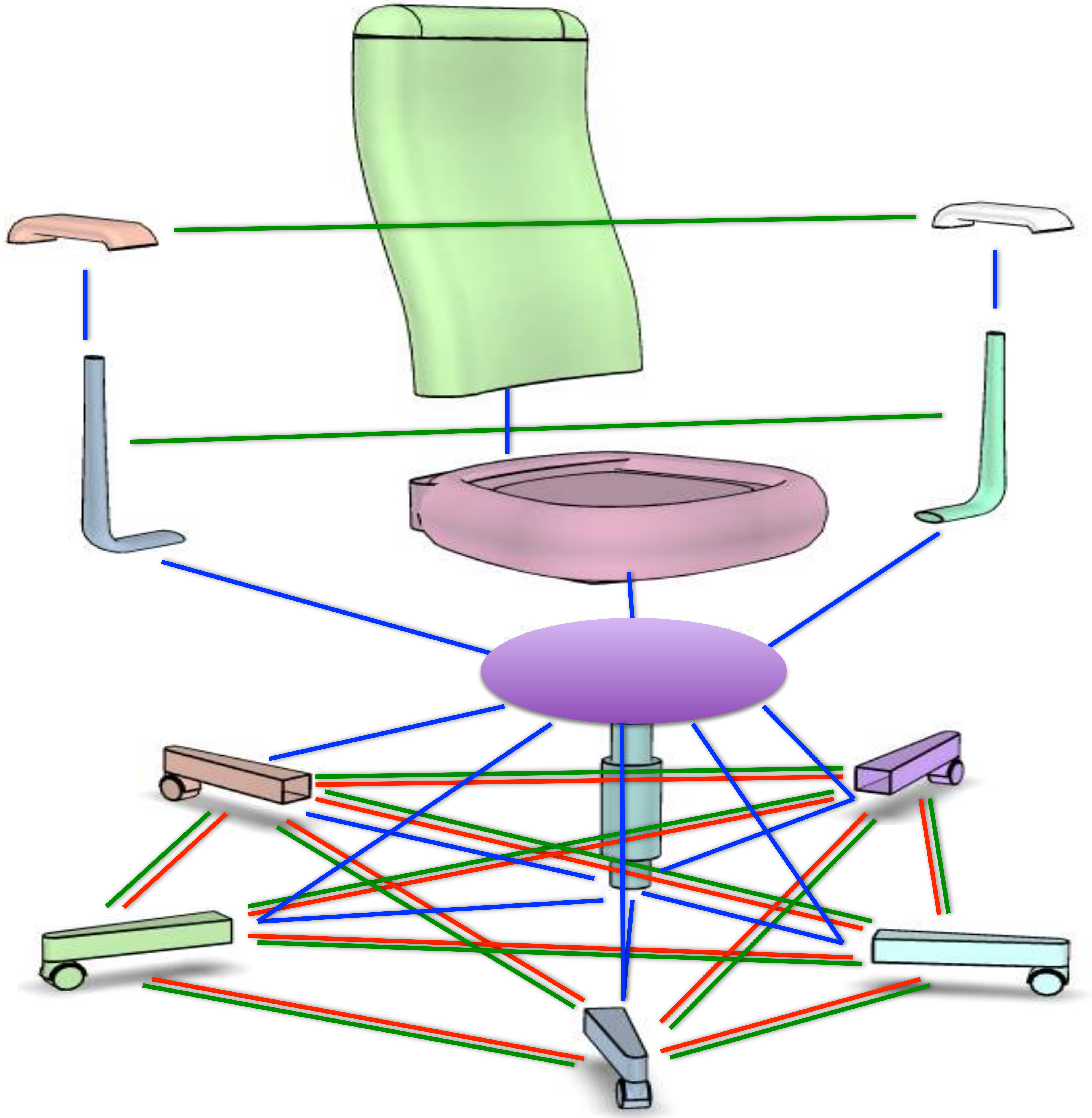
Bottom-up graph contraction



Two operations:

Grouping by symmetry

Bottom-up graph contraction



Two operations:

Grouping by symmetry

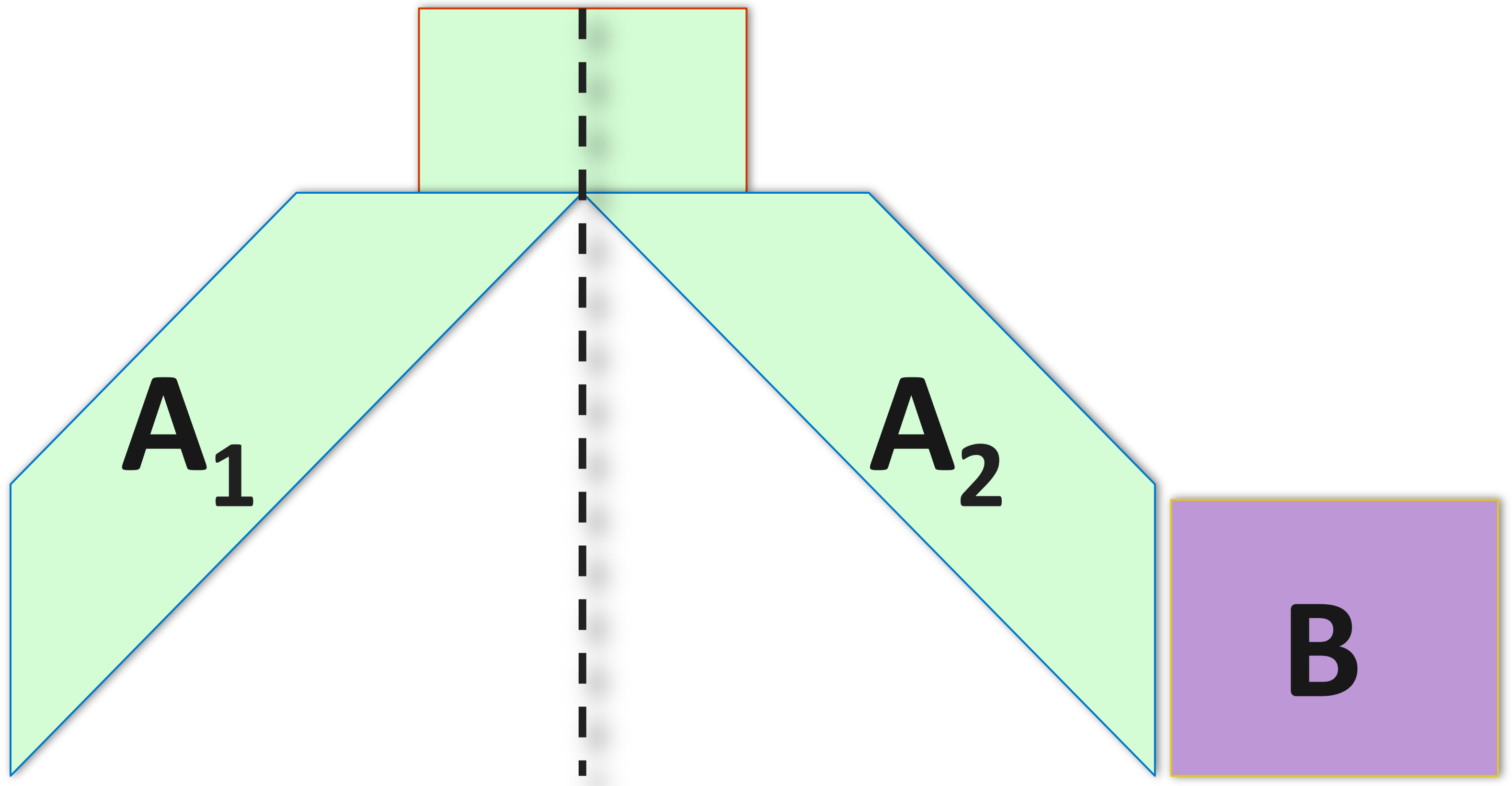
Assembly by proximity

How to order contractions?

- Guiding principles
  - Perceptual grouping: Gestalt law of symmetry
  - Compactness of representation: Occam's Razor
  - Results in a set of "precedence rules"

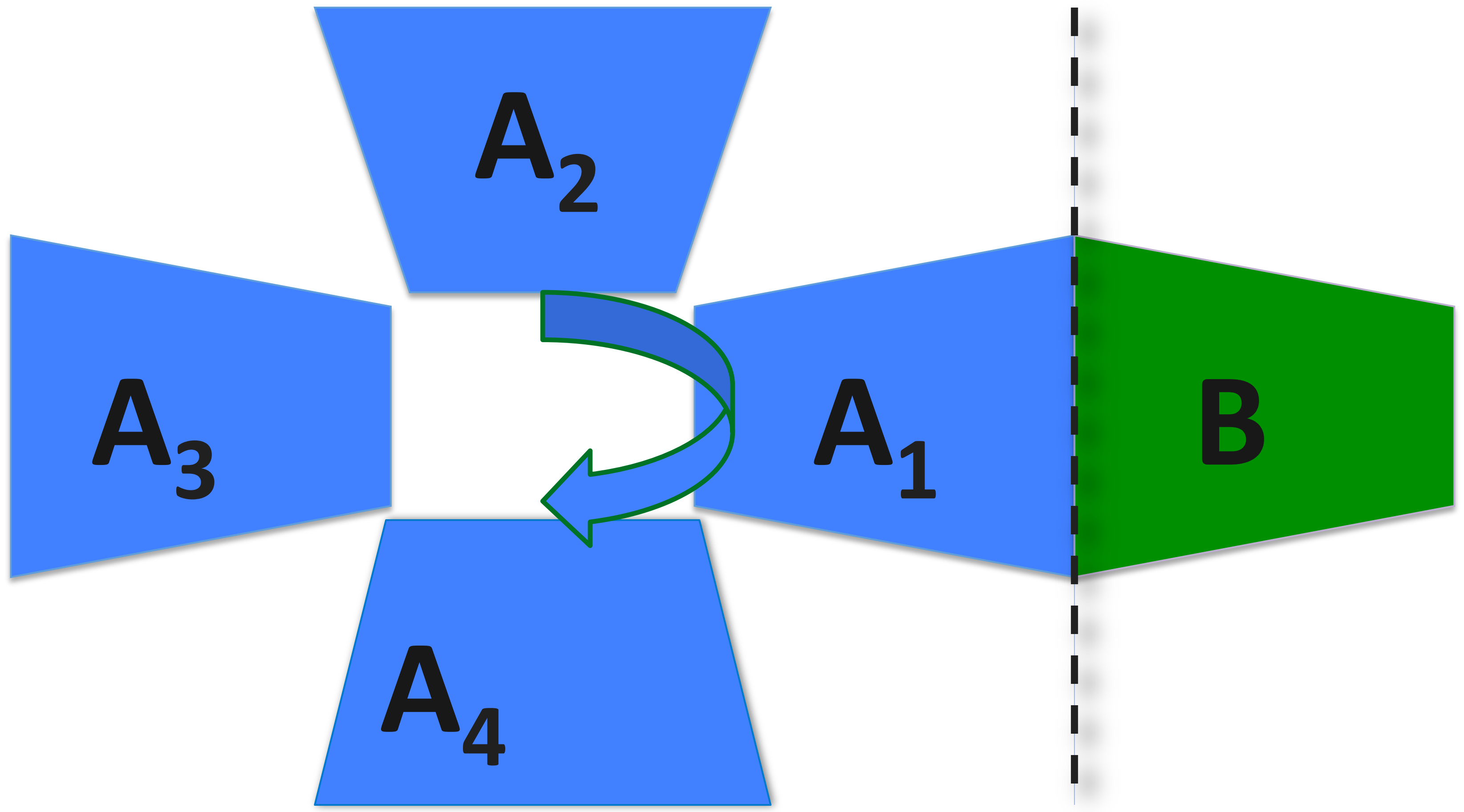
Example of precedence rules

- Grouping-assembly mixing rules, e.g.,
  - symmetry grouping takes precedence over assembly



Example of precedence rules

- Symmetry grouping rules, e.g.,
  - rot-symmetry takes precedence over ref-symmetry



unless

Example of precedence rules

- Symmetry grouping rules, e.g.,
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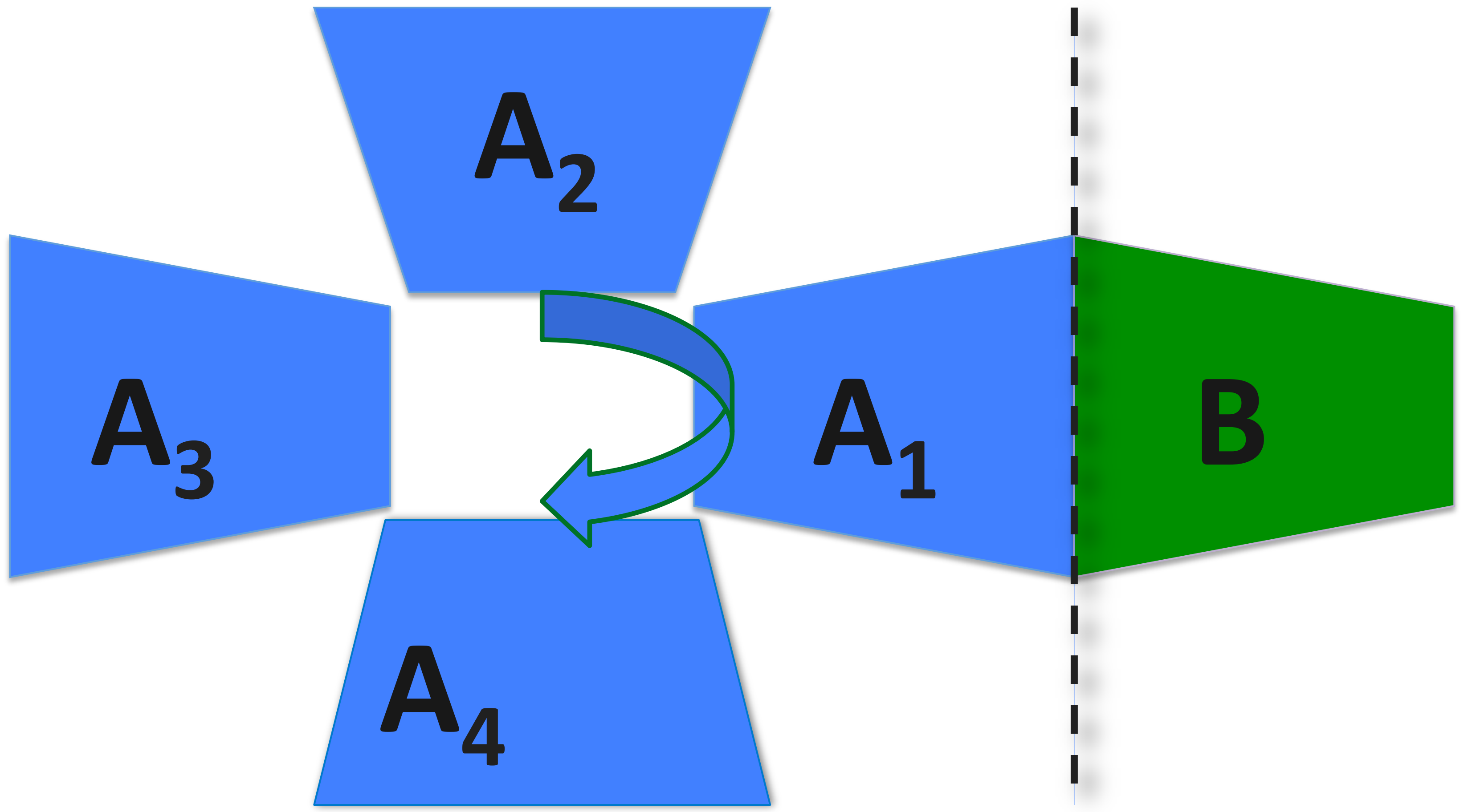
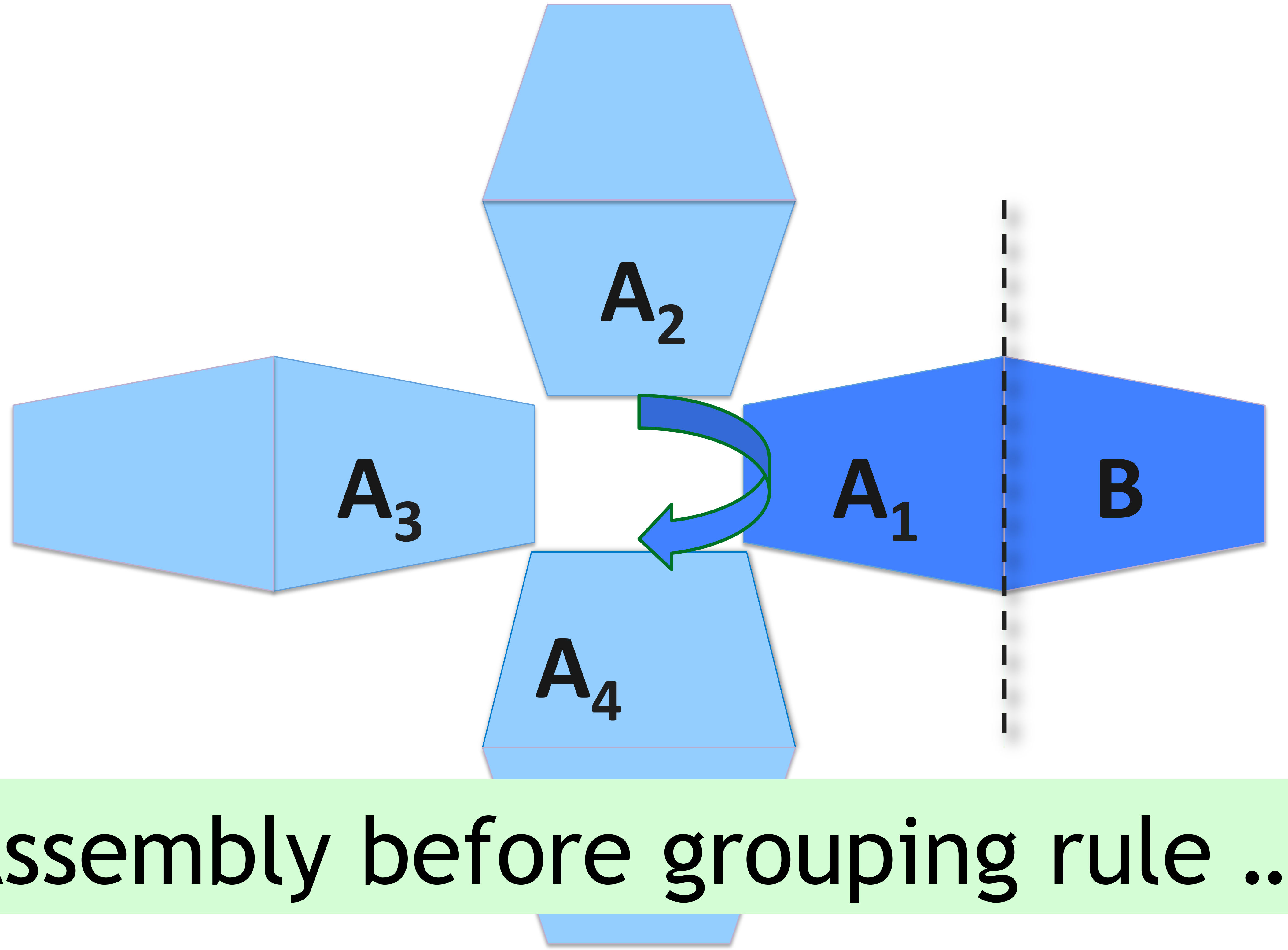
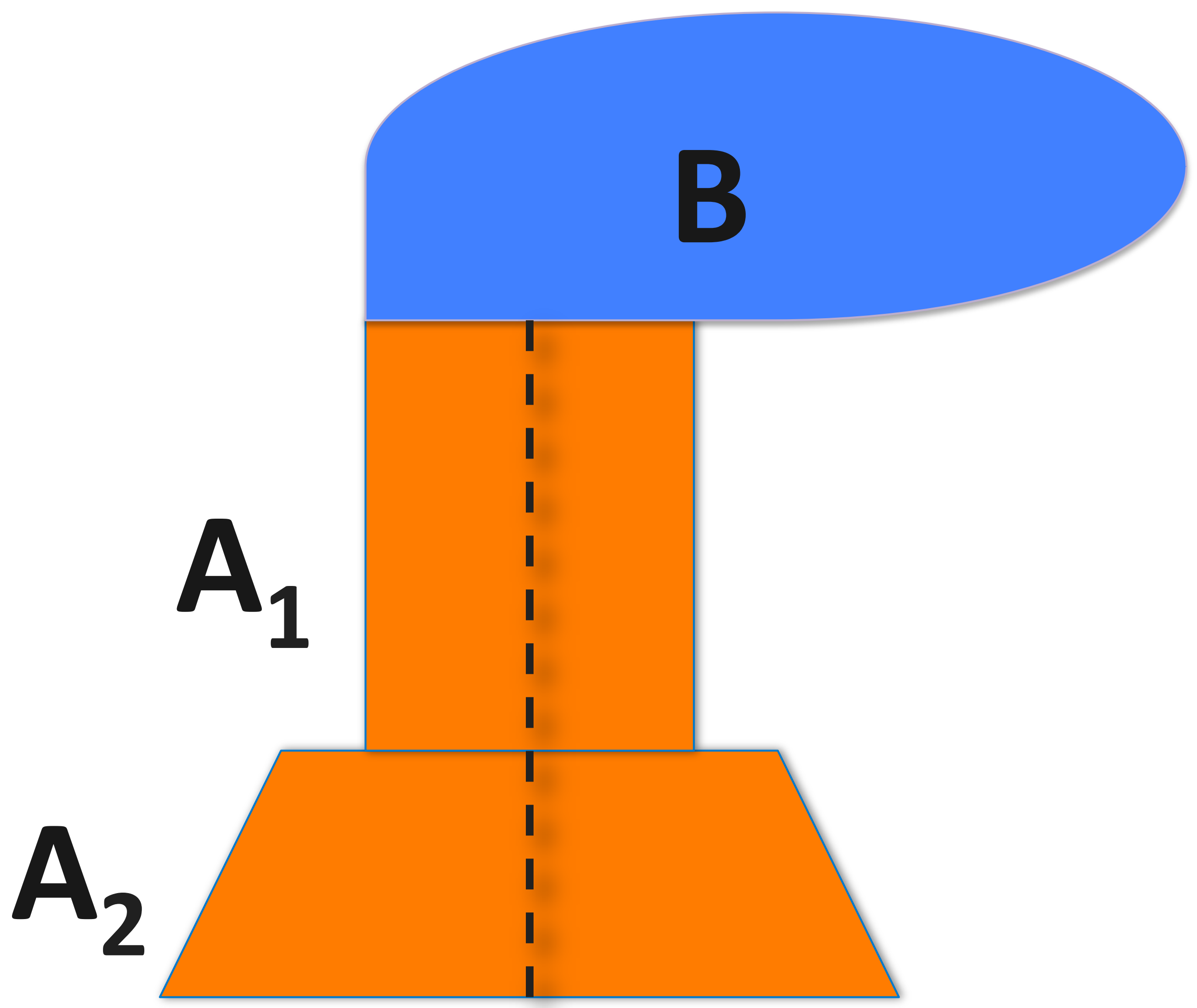




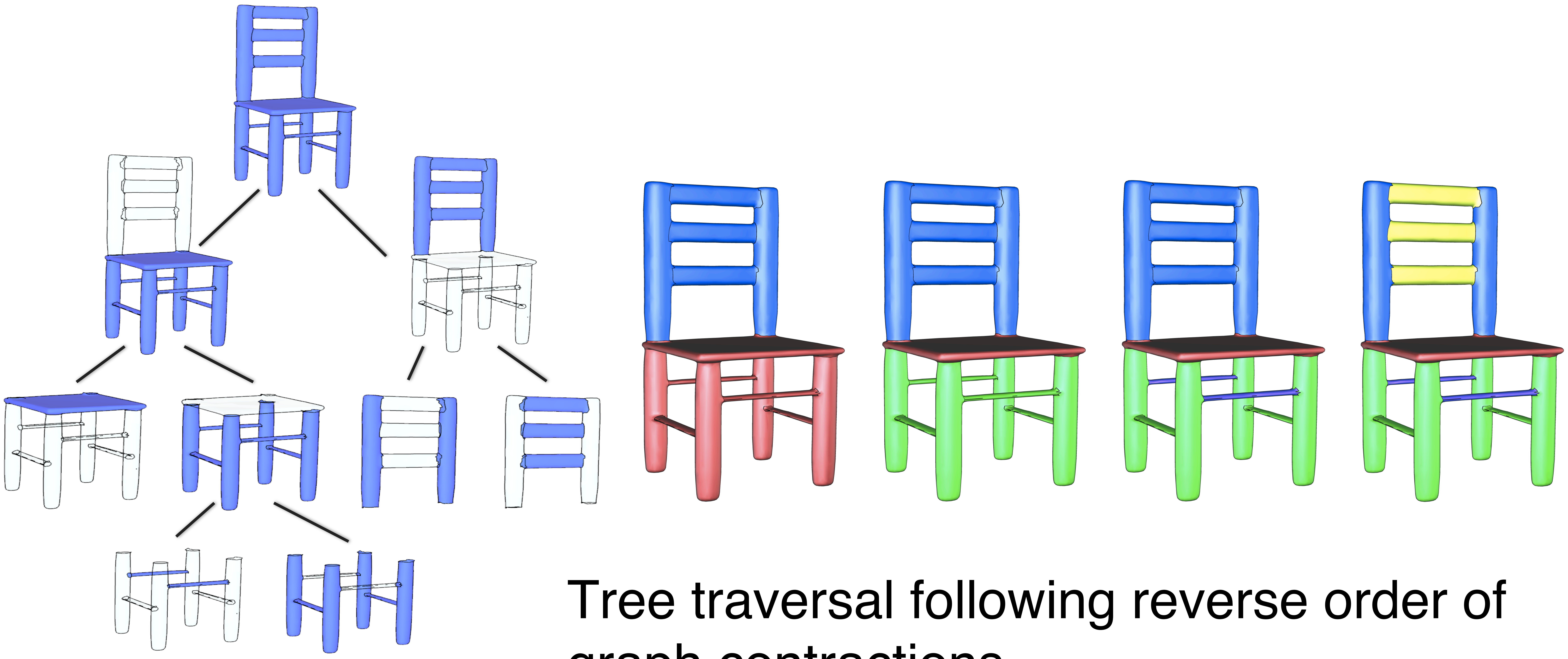
Assembly before grouping rule …

Example of precedence rules

- Assembly rules, e.g.,
  - assemble parts that preserve more symmetries first



App: hierarchical segmentation



Tree traversal following reverse order of graph contractions

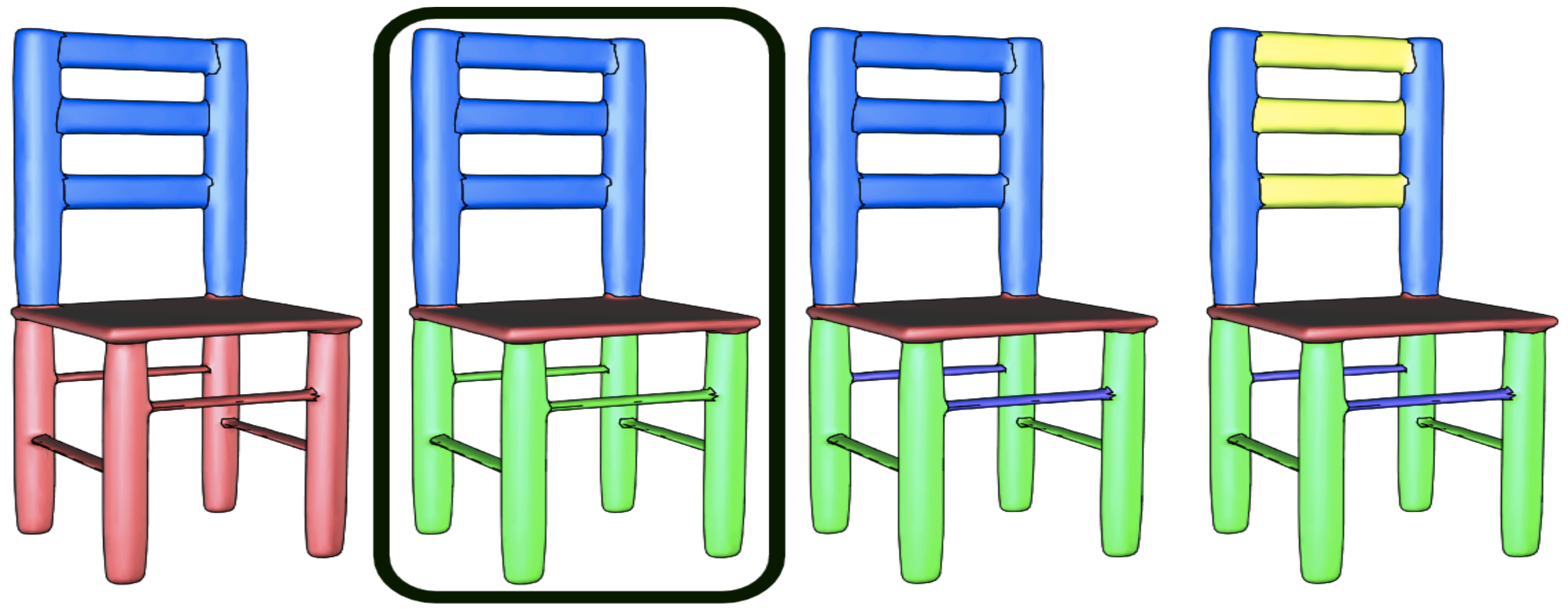
App: structural editing

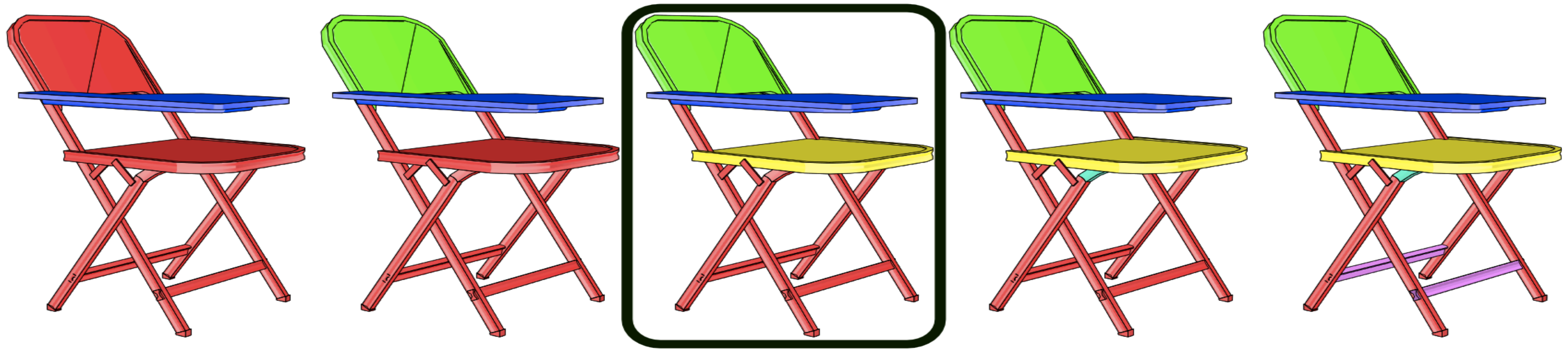
Structural Shape Editing

Limitations

- Construction is not the result of an optimization, but based on hand-crafted precedence rules

- **Inconsistent hierarchies** for objects in same class

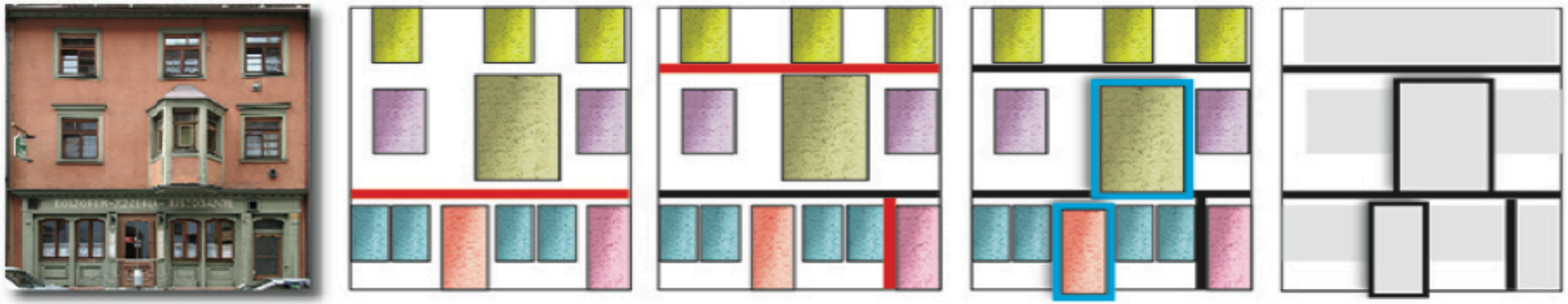




Symmetry maximization [Zhang et al. 2013]

Goal: a generative model that best explains a structure

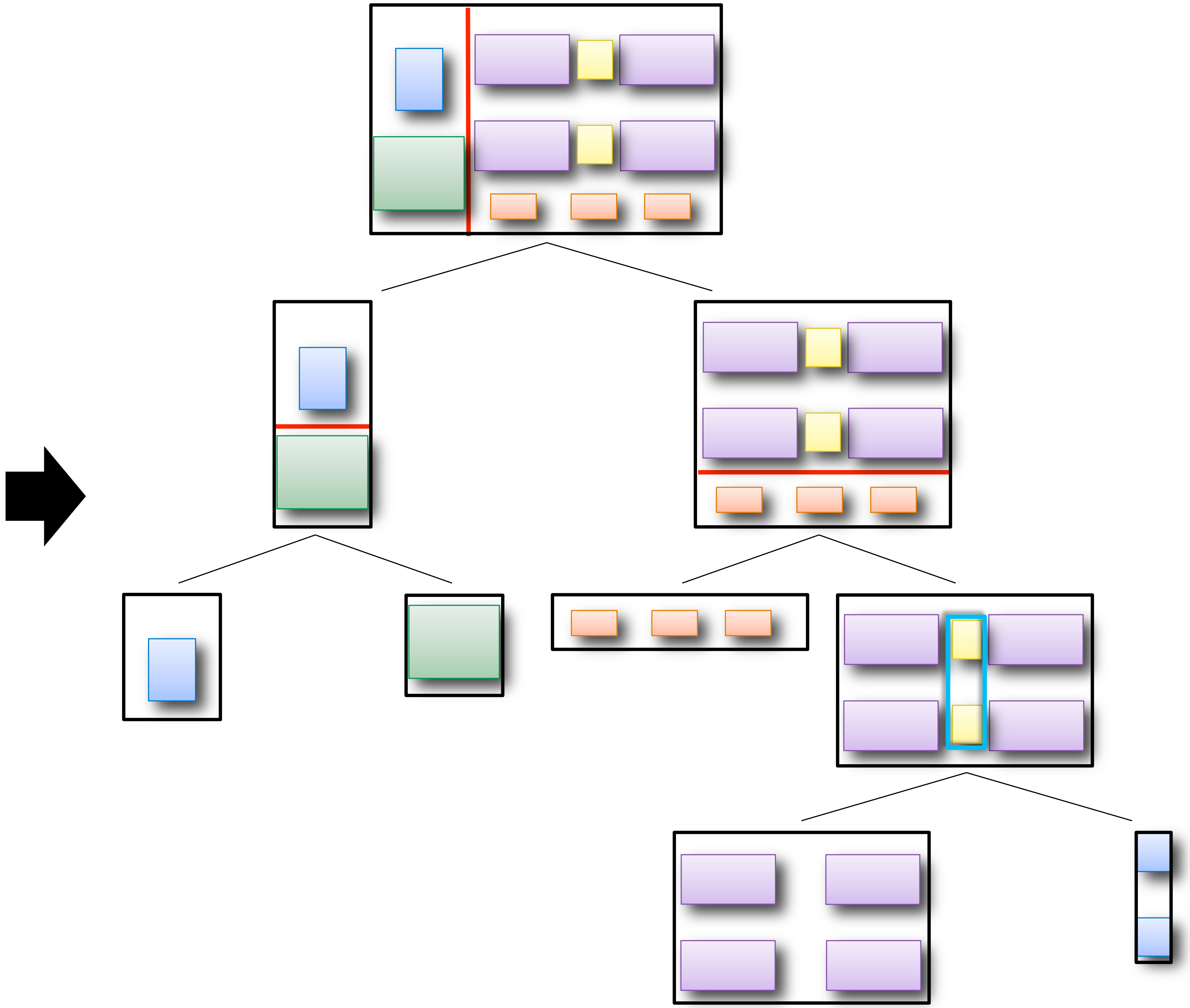
- Explain irregular 2D facades via symmetry maximization
- Use hierarchical decomposition as generative model



- Decomposition stops when reaching a regular grid (maximal symmetry) as it requires no explanation

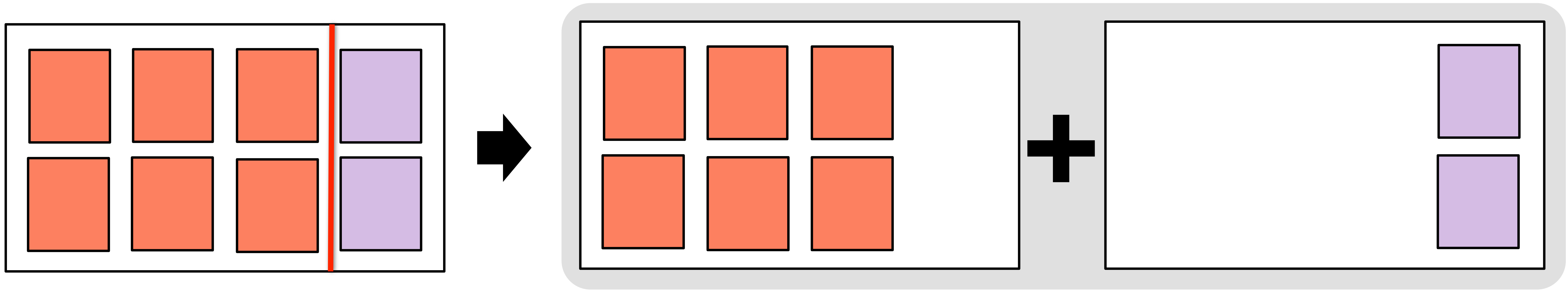
Structural hierarchy

- Hierarchical 2-way decomposition



Two operations

- 2-way splits along two lateral directions

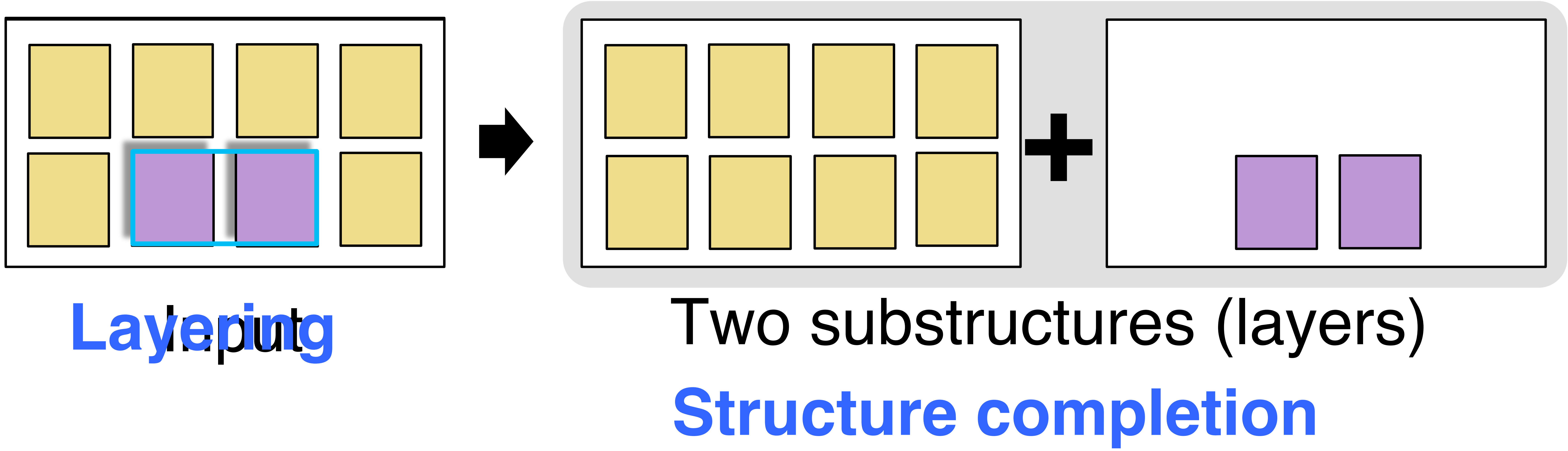


Input Split

Two substructures

Two operations

- Layering: “split” along depth direction

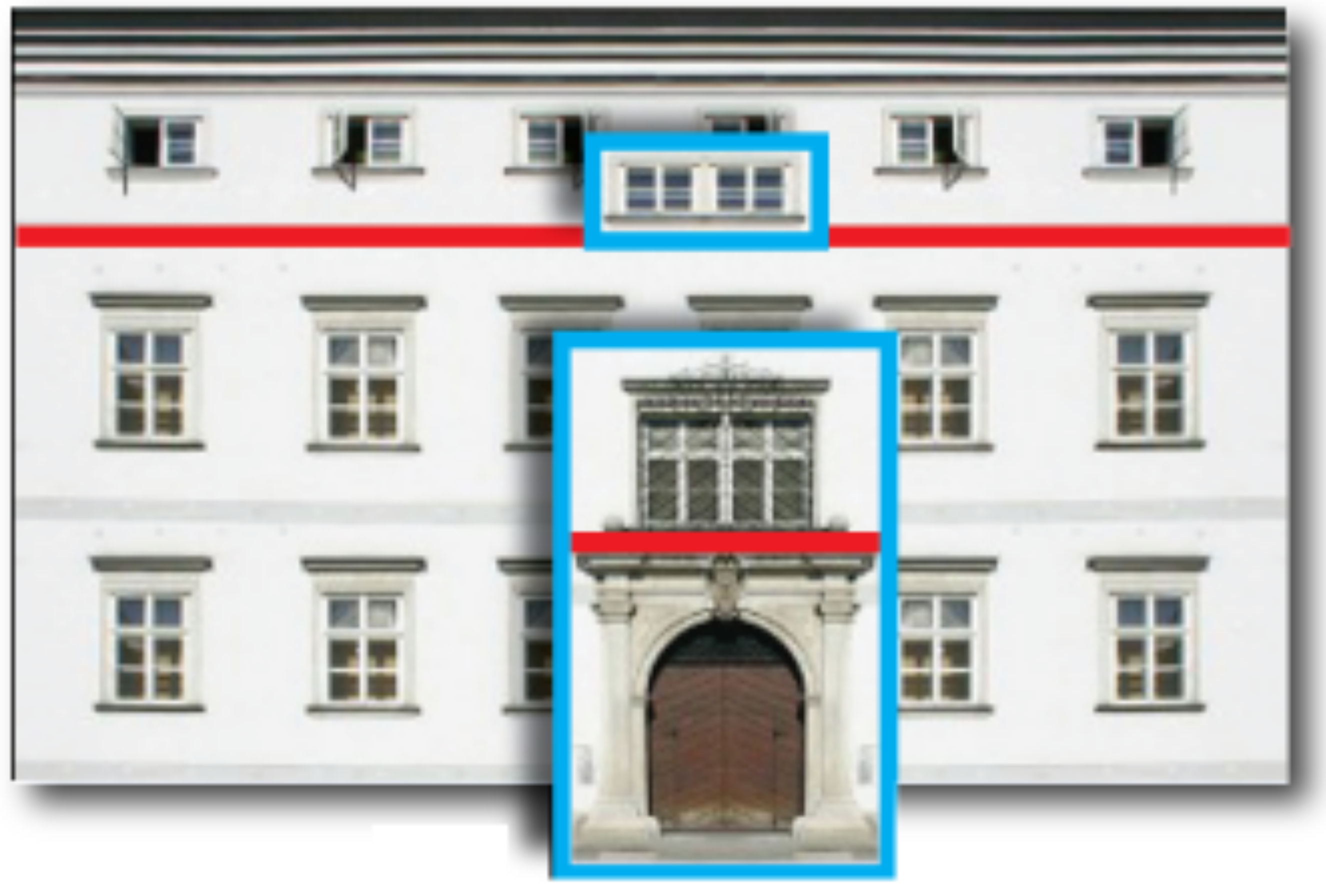


Layering + split vs. split only

- Layering leads to more compact (simpler) explanation

Input

Split only
8 ops.



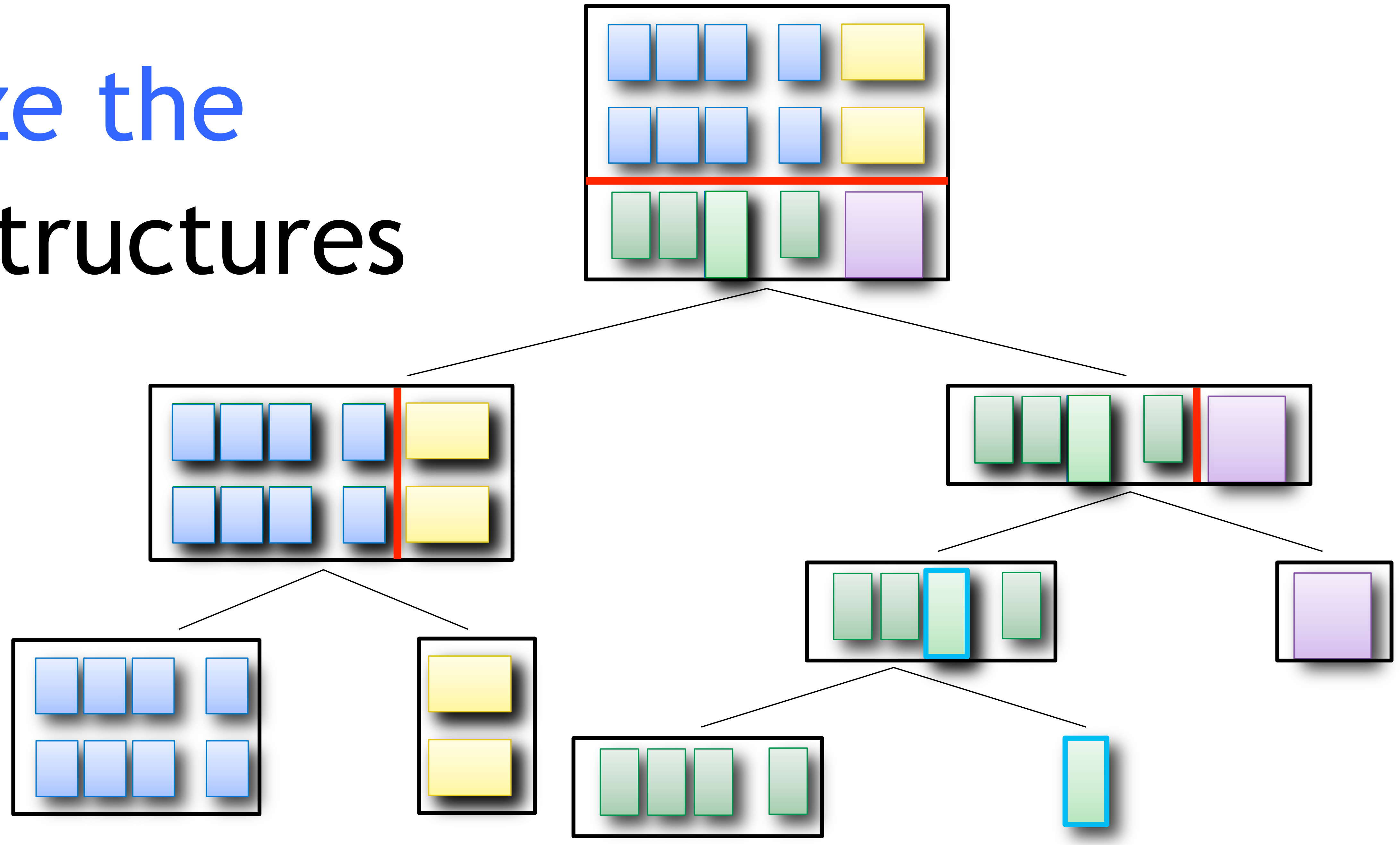
Split + Layering
4 ops.

Best explanation via SYMAX

Key ideas:

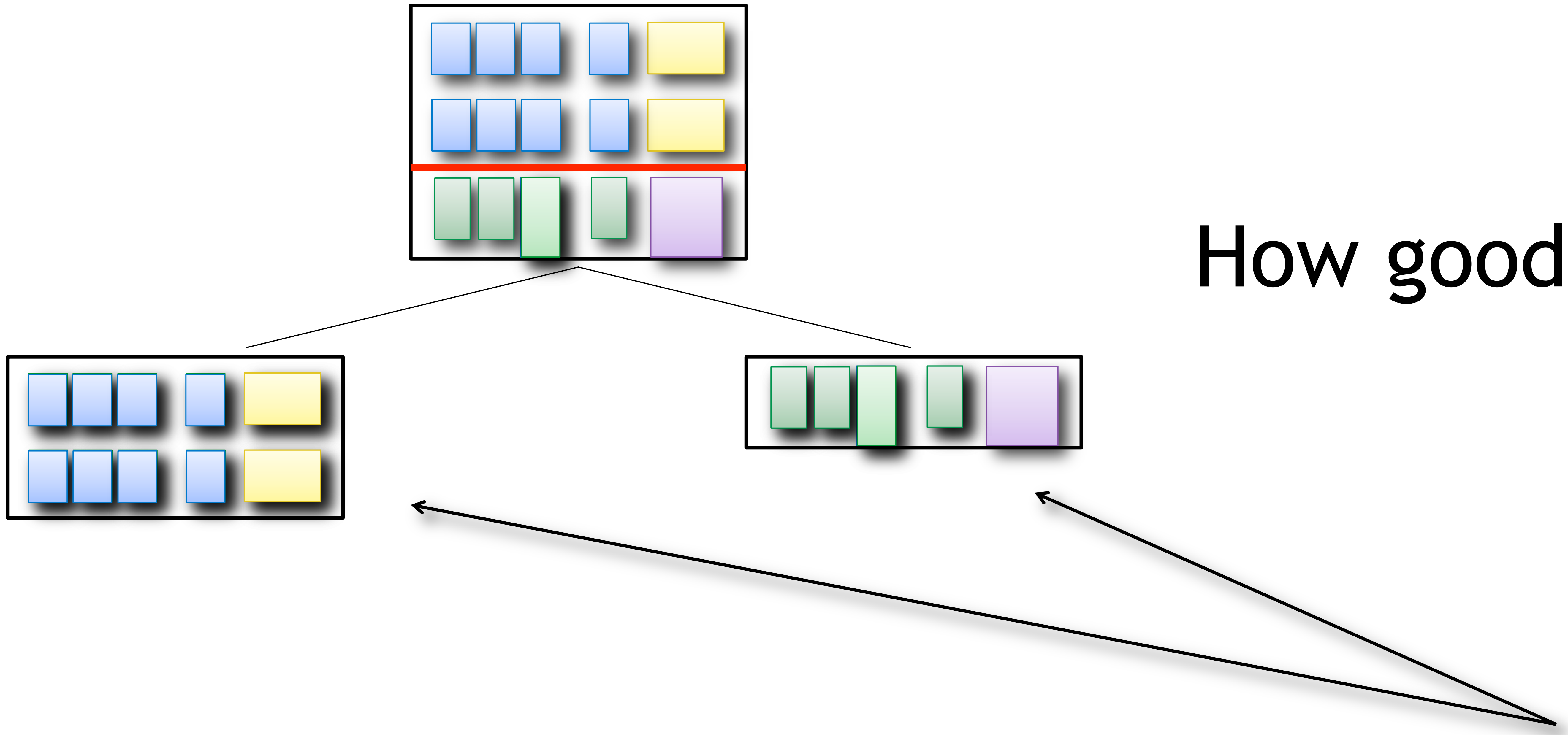
- Best explanation = simplest explanation = fewest decompositions
- Decomposition should then maximize the symmetry (SYMAX) of resulting substructures

SYMAX is consistent with
Gestalt law of symmetry



Symmetry maximization

- Symmetry maximization at each decomposition



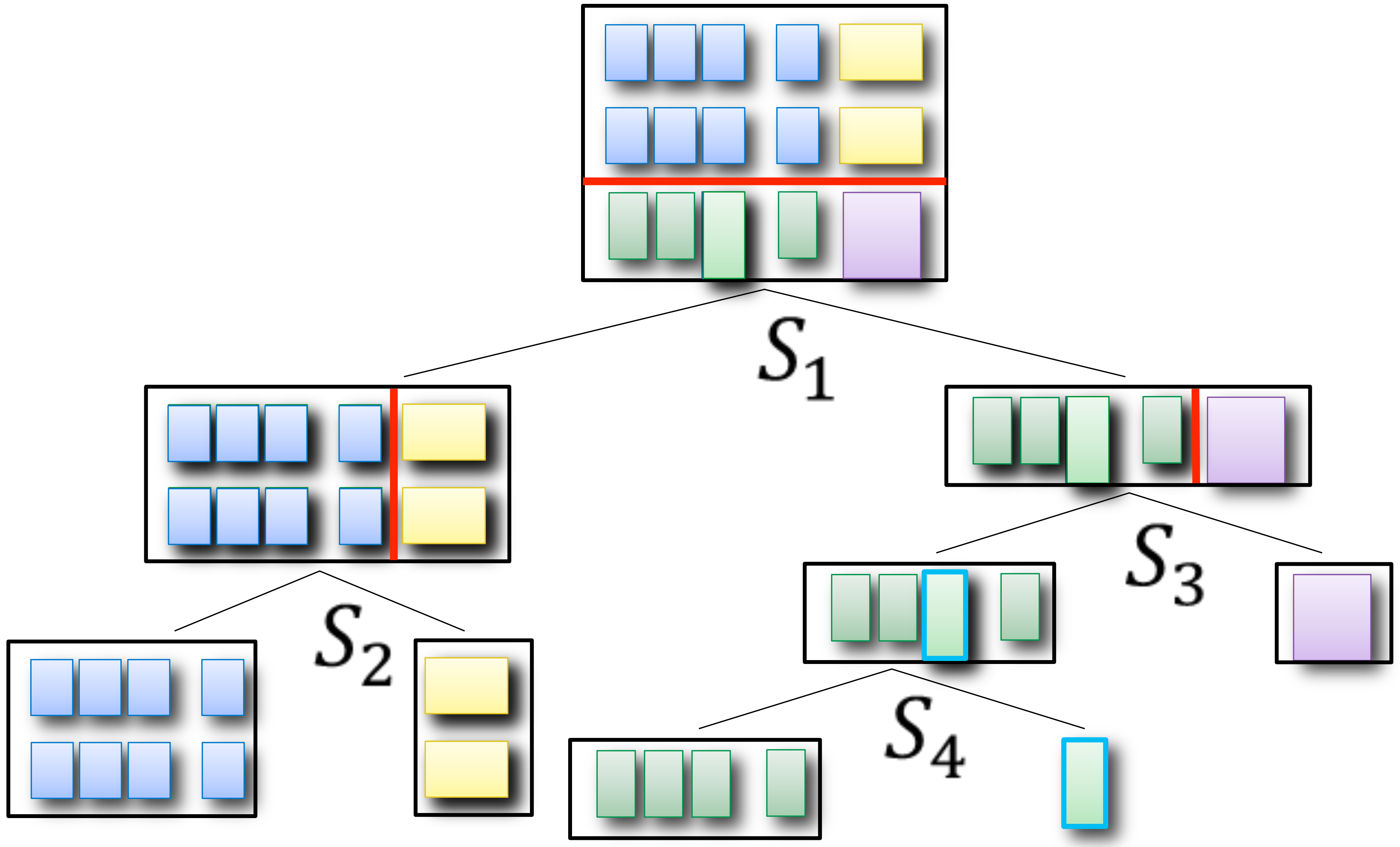
How good is the decomposition

=

How symmetric the two substructures are

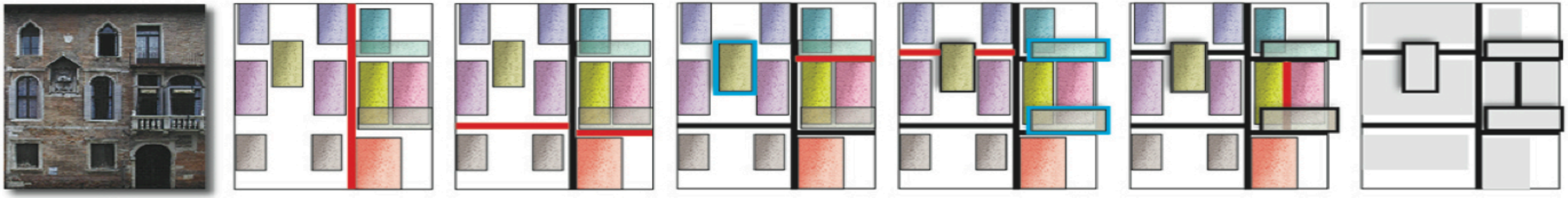
Objective function

- Sum of **symmetry measures** at all internal nodes



$$\max.\ \Sigma = S_1 + S_2 + S_3 + S_4$$

SYMAX vs. symmetry hierarchy



SYMAX

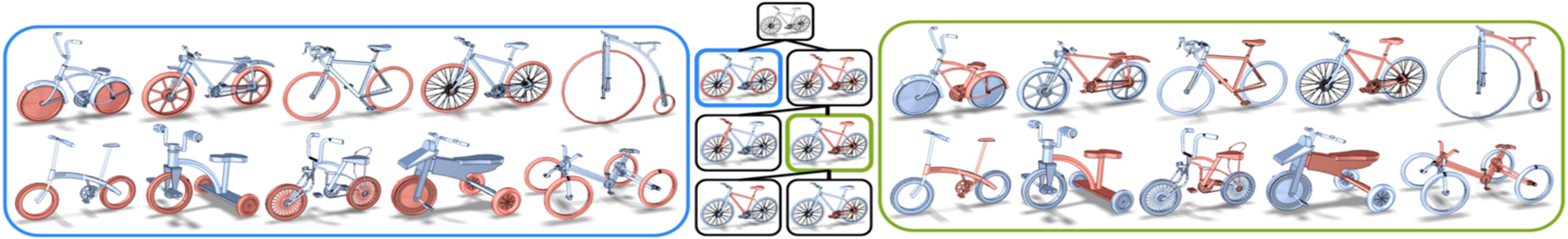
- involves explicit optimization
- symmetry hierarchy with an objective function

Both still confined to analyzing individual models

Co-hierarchy [van Kaick et al. 2013]

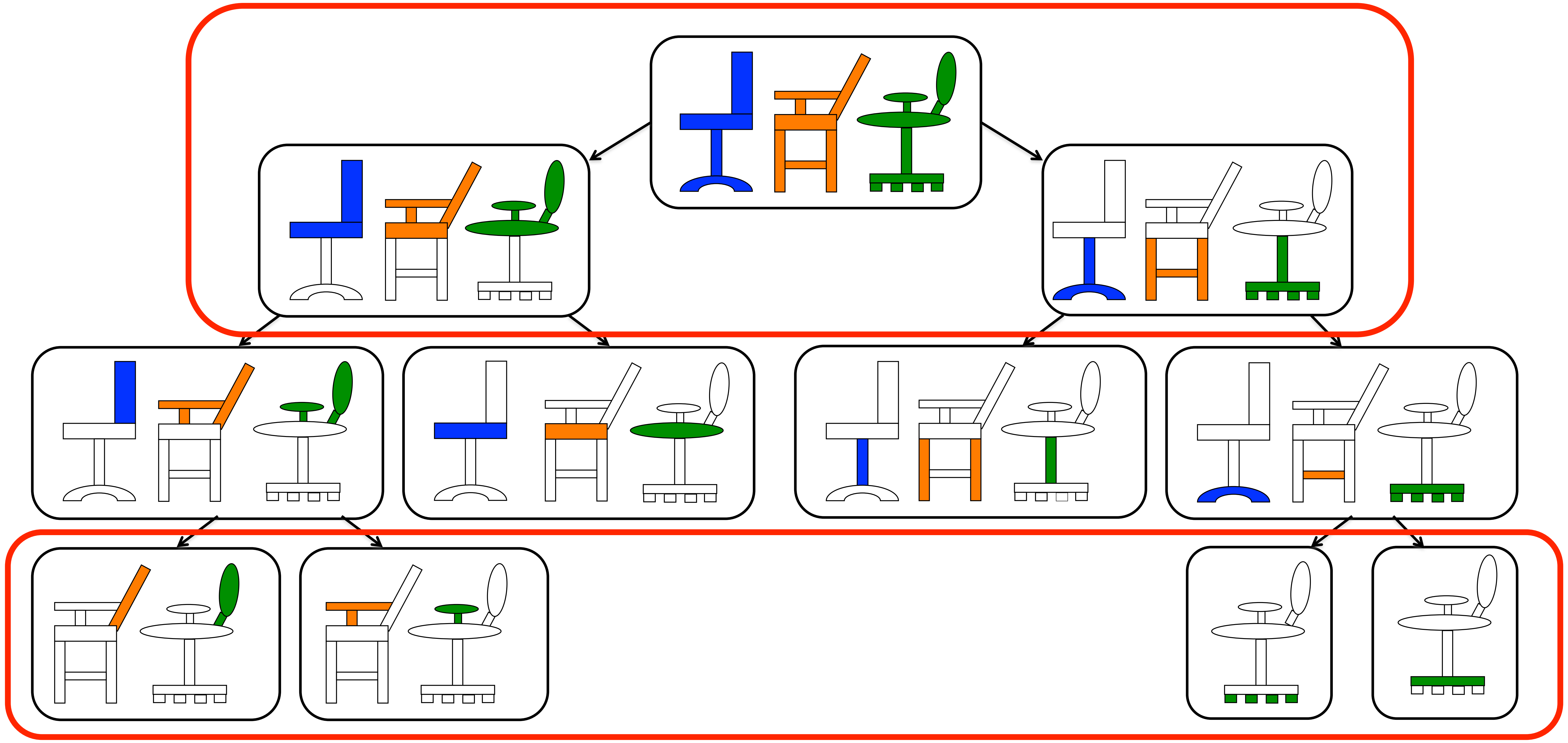
Goal: obtain a structural hierarchy that best explains a **set of objects** belonging to the same class

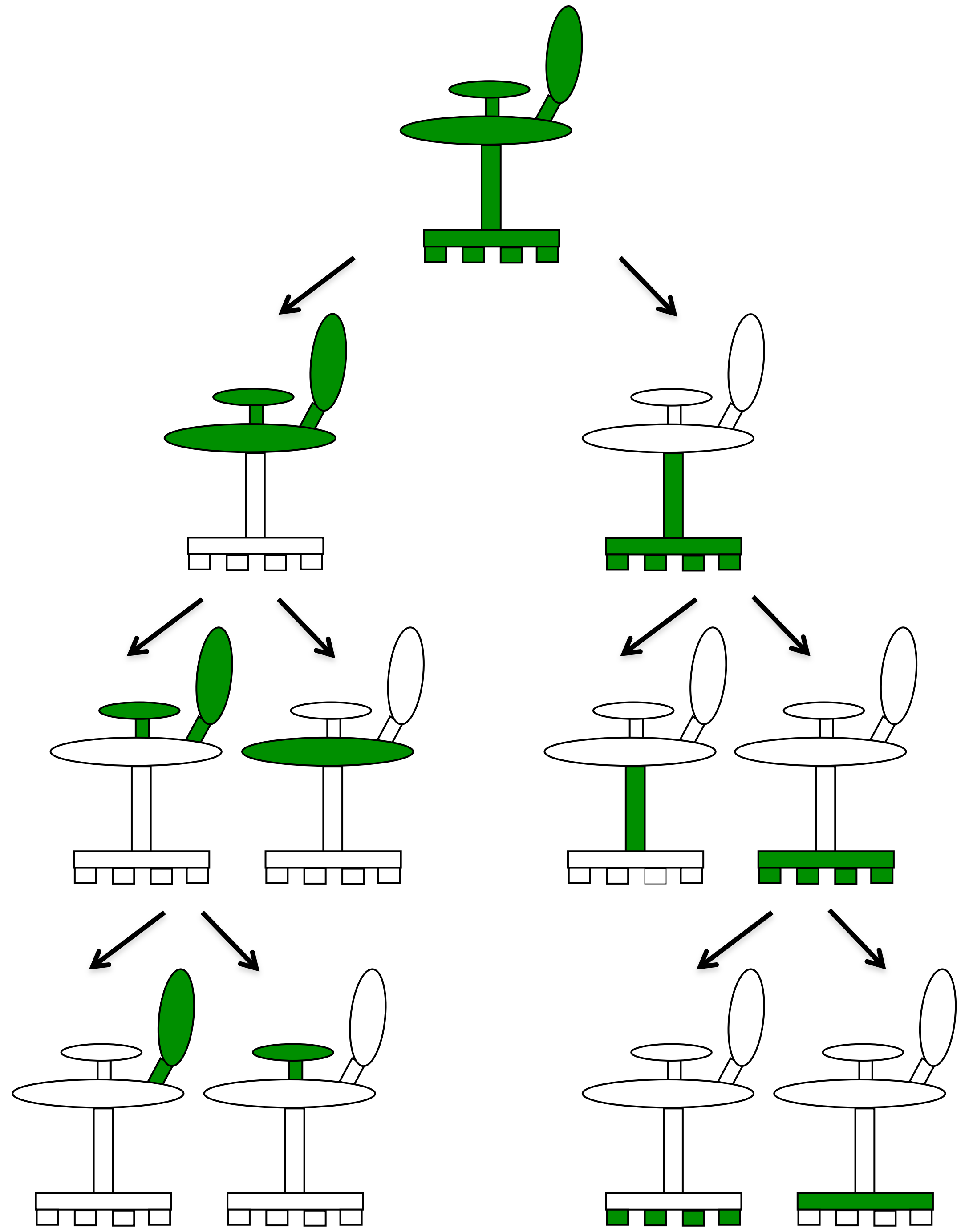
- Extends symmetry hierarchy to **co-analysis** of a set
- A **unified explanation** of the shape structures



Similarity and diversity

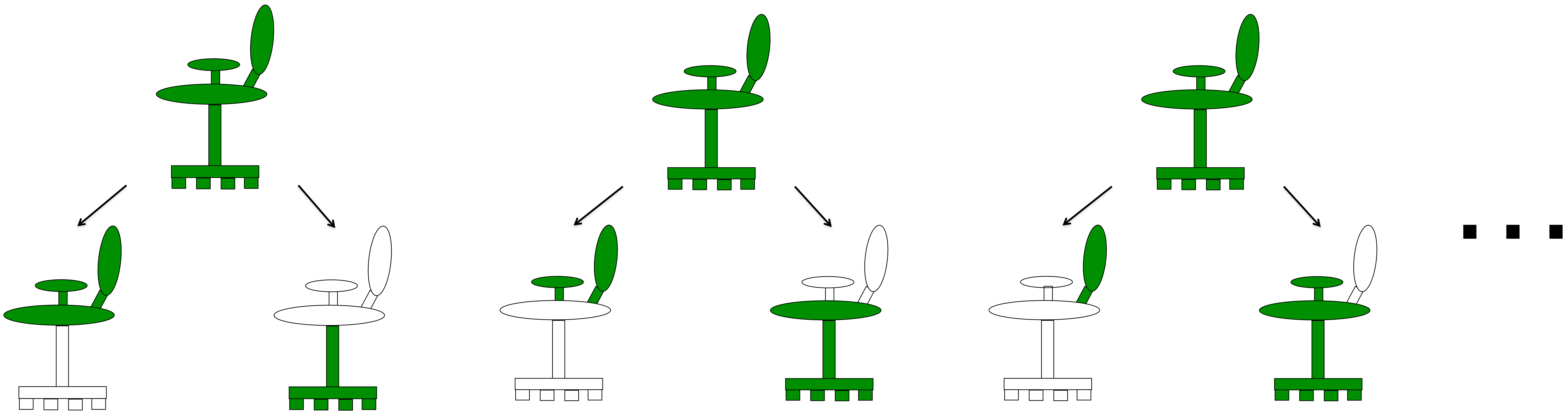
- **Coarse level:** similarity across set





- **Finer level:** individual shape variations

Challenges



Each object can have **many possible** hierarchies.

Need to **select** one hierarchy per shape.

Challenges

There can be much **geometric variability** in the set.

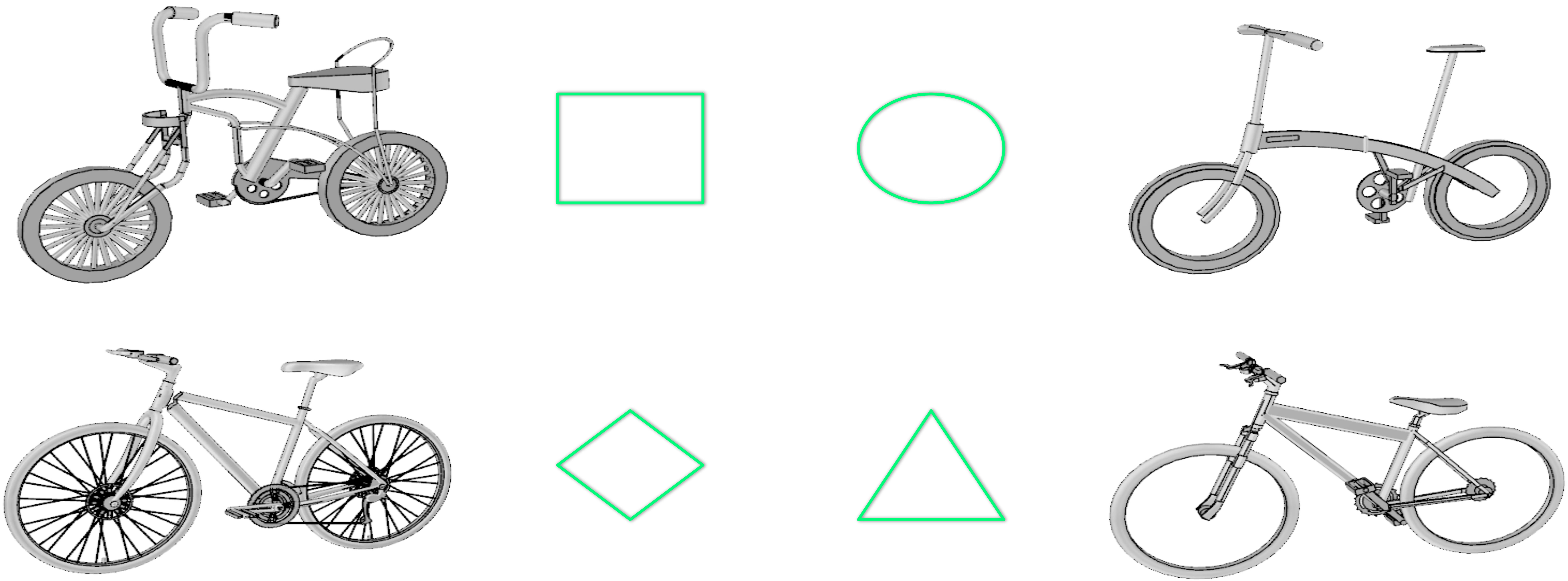
Need to go beyond geometry and focus on shape **structures.**

Challenges

There can also be much **structural variability**; a single explanation cannot be sufficient

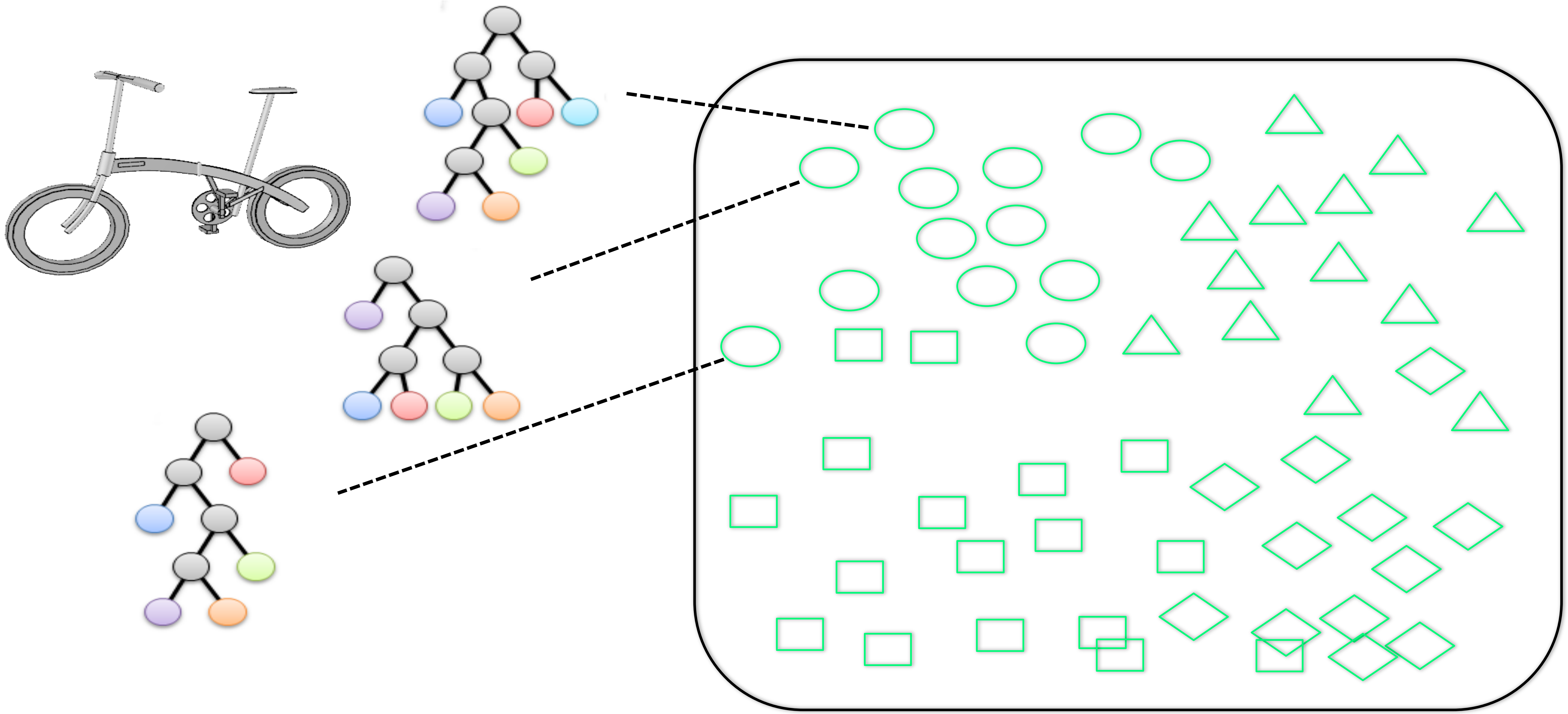
We account for that by **clustering** the hierarchies.

Algorithm illustration



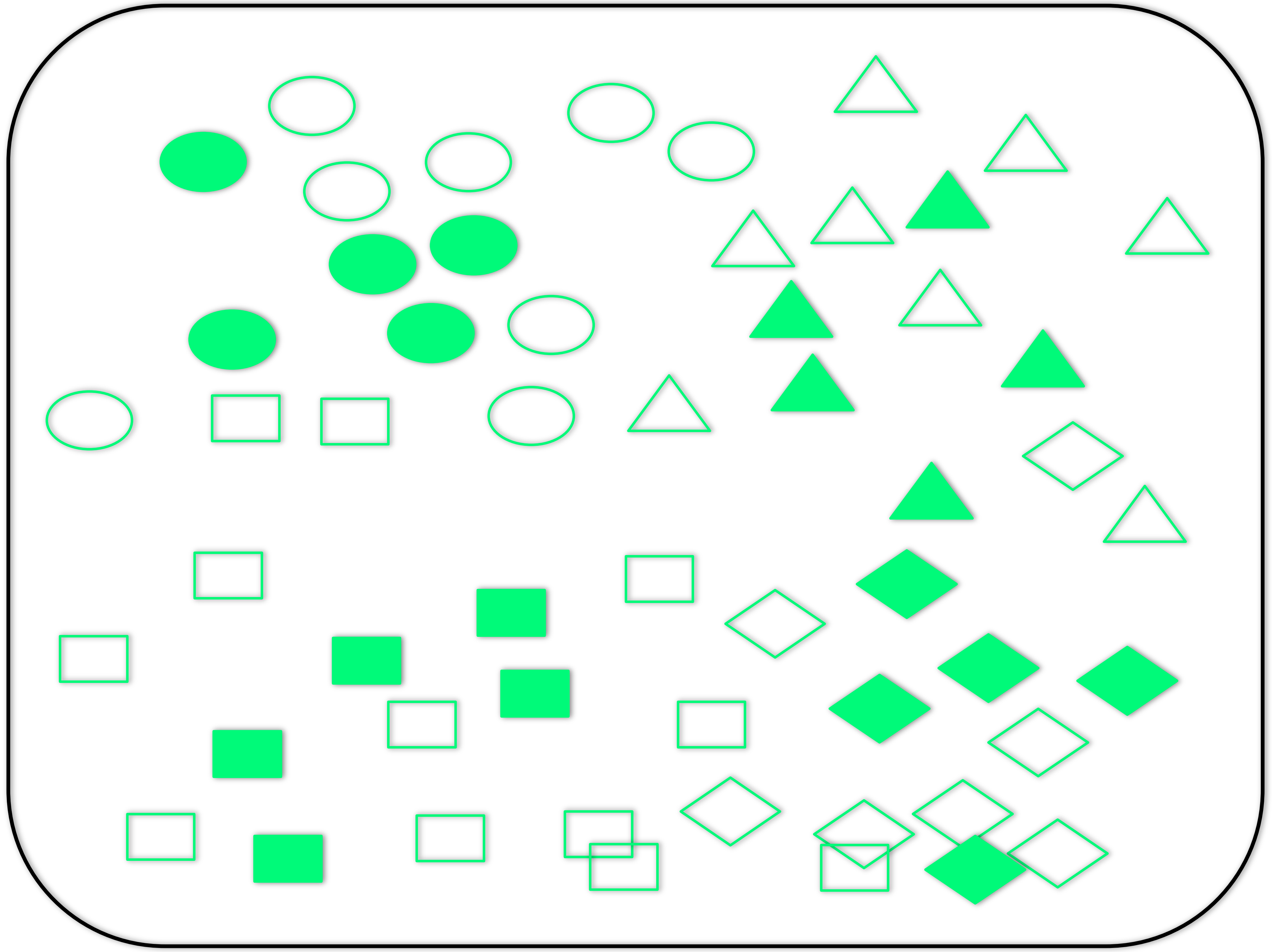
Using a minimal set of four shapes

Per-shape symmetry hierarchies



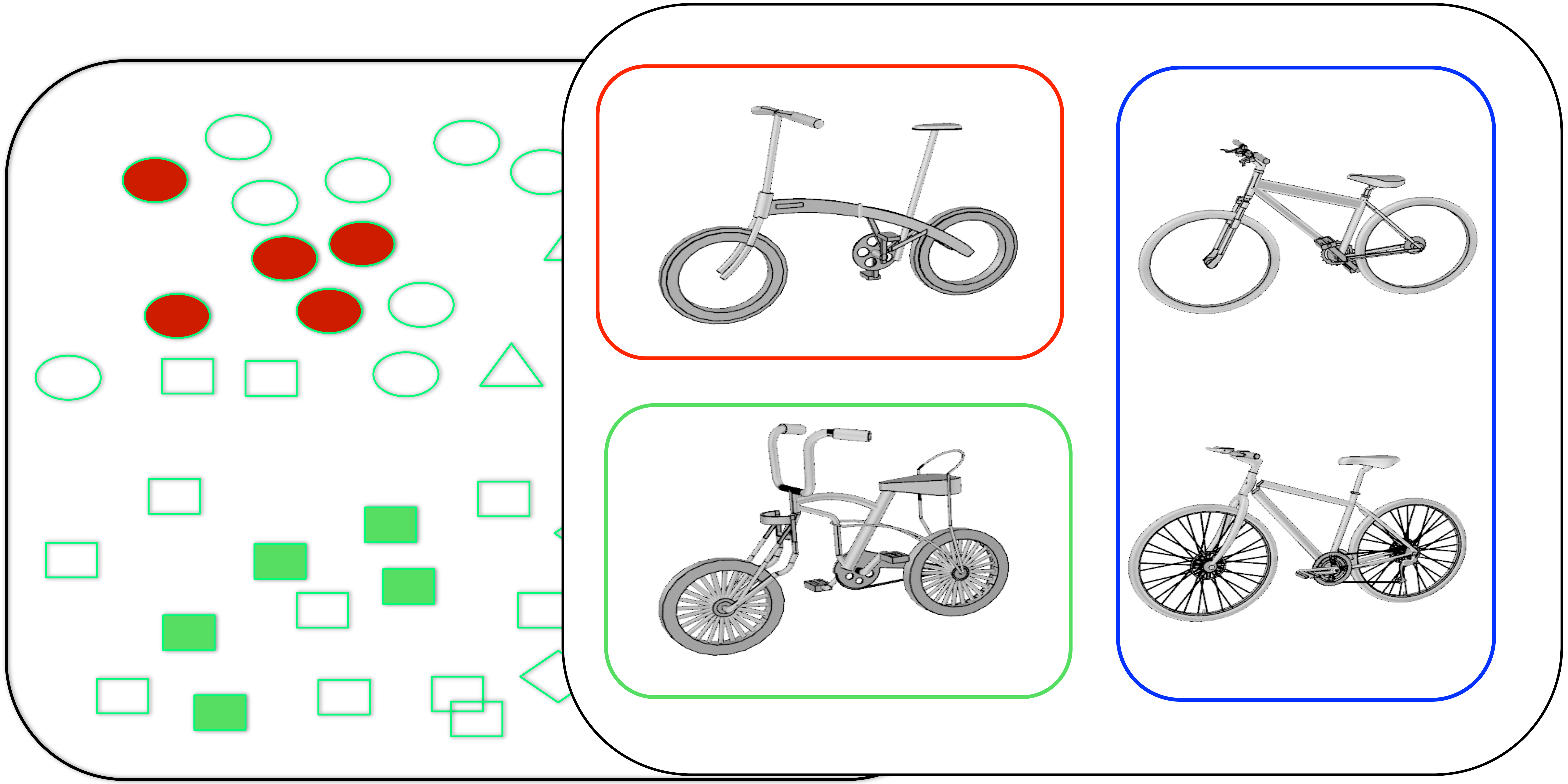
Compute symmetry hierarchies per shape

Sampling



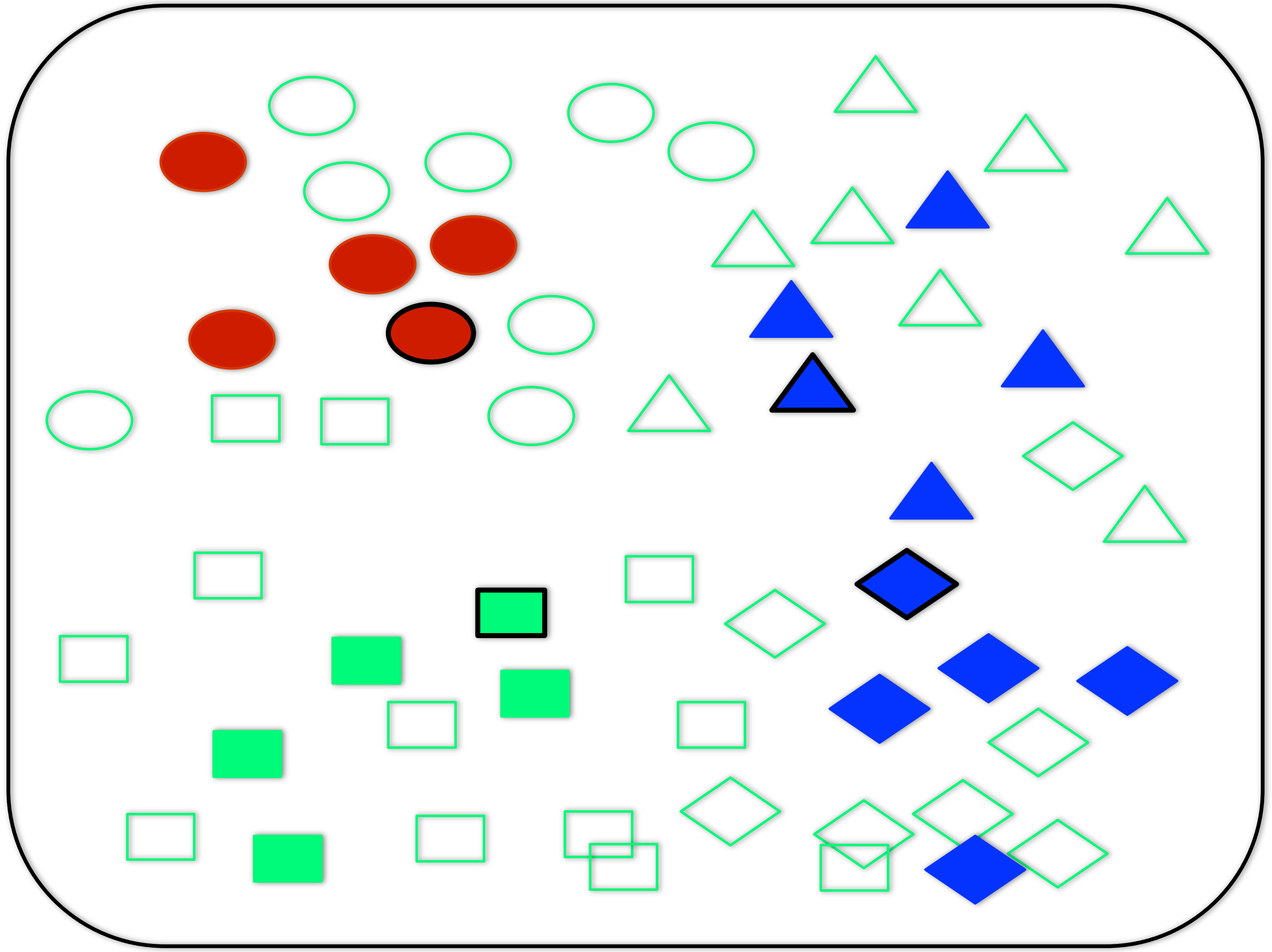
Sample from population of per-shape hierarchies

Key problem: clustering



Multi-instance clustering: cluster the shapes while each shape has multiple instances (the samples)

… and then select

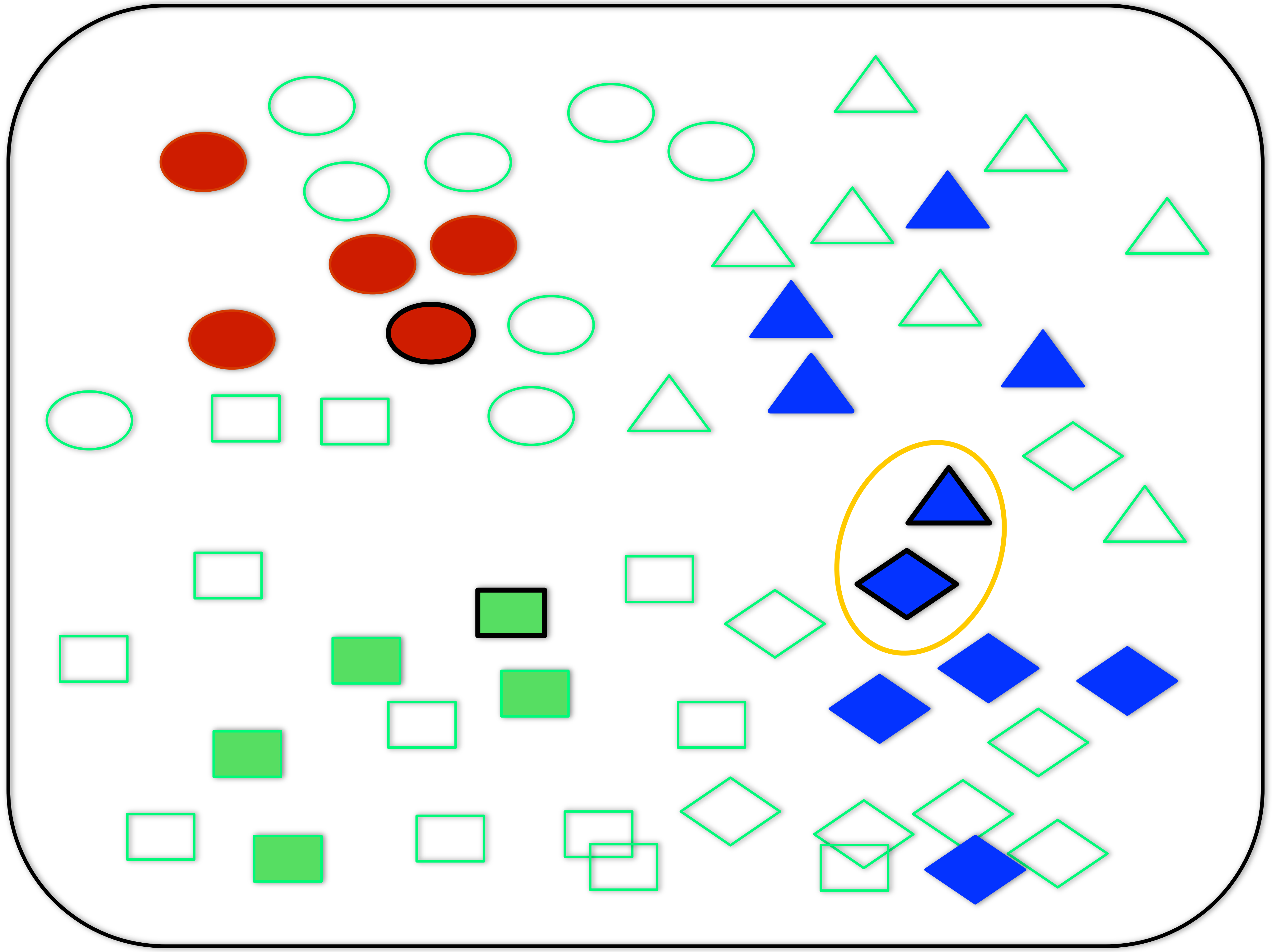


Select **one representative** hierarchy **per shape**

Objective of cluster-and-select

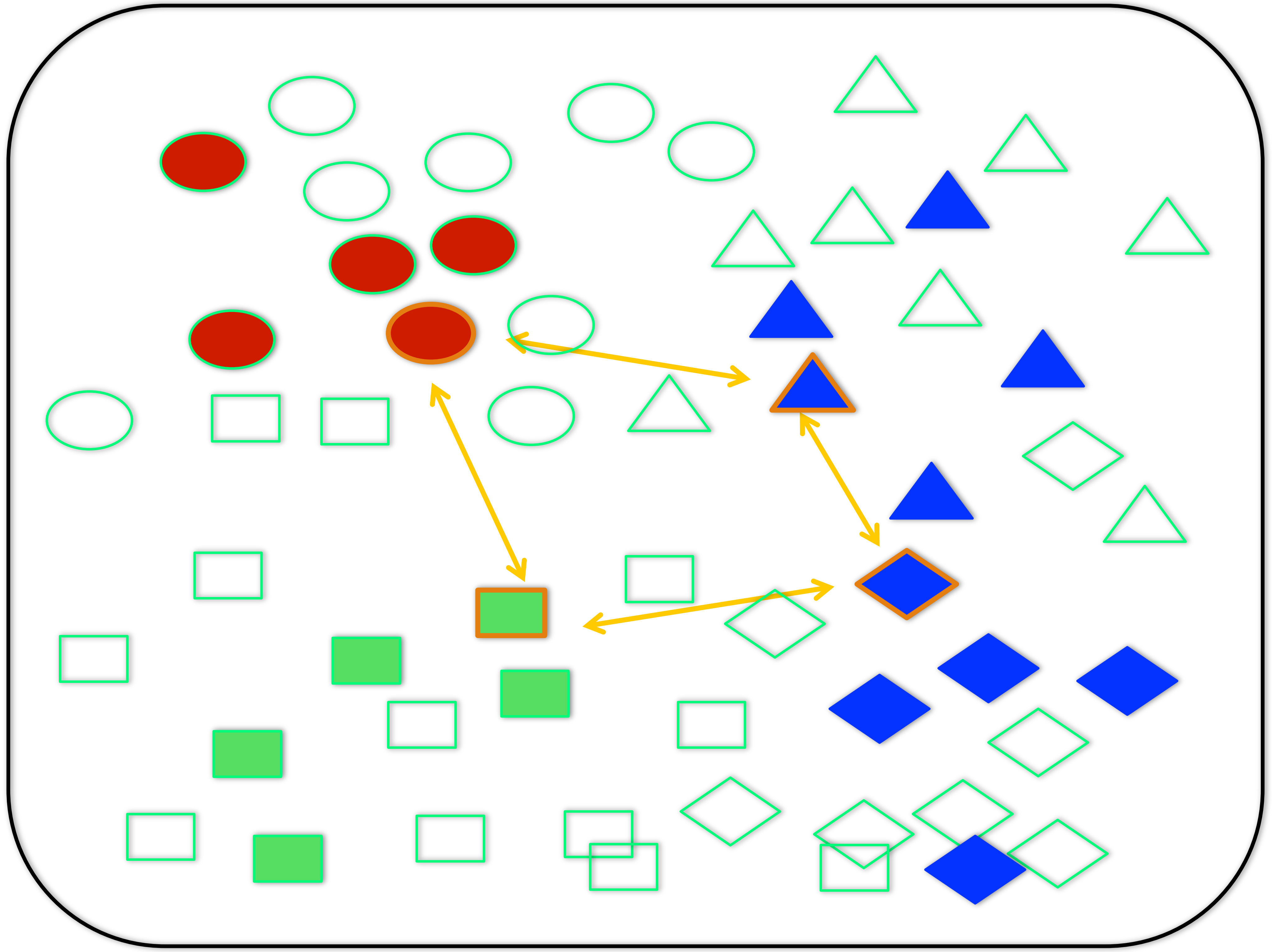
- Traditional clustering: maximize within-cluster similarity and between-cluster **dissimilarity**
- In our problem: all shapes in the set are related
  - So wish to discover maximal **similarity among all shapes**
  - But still allow clusters to characterize structural variability
  - Trick in **representative selection:** selections should **maximize both within-cluster and between-cluster similarities**
  - Then **resample hierarchies (and then cluster-select) close to the selections** so the clusters as a whole also get closer

Representative selection



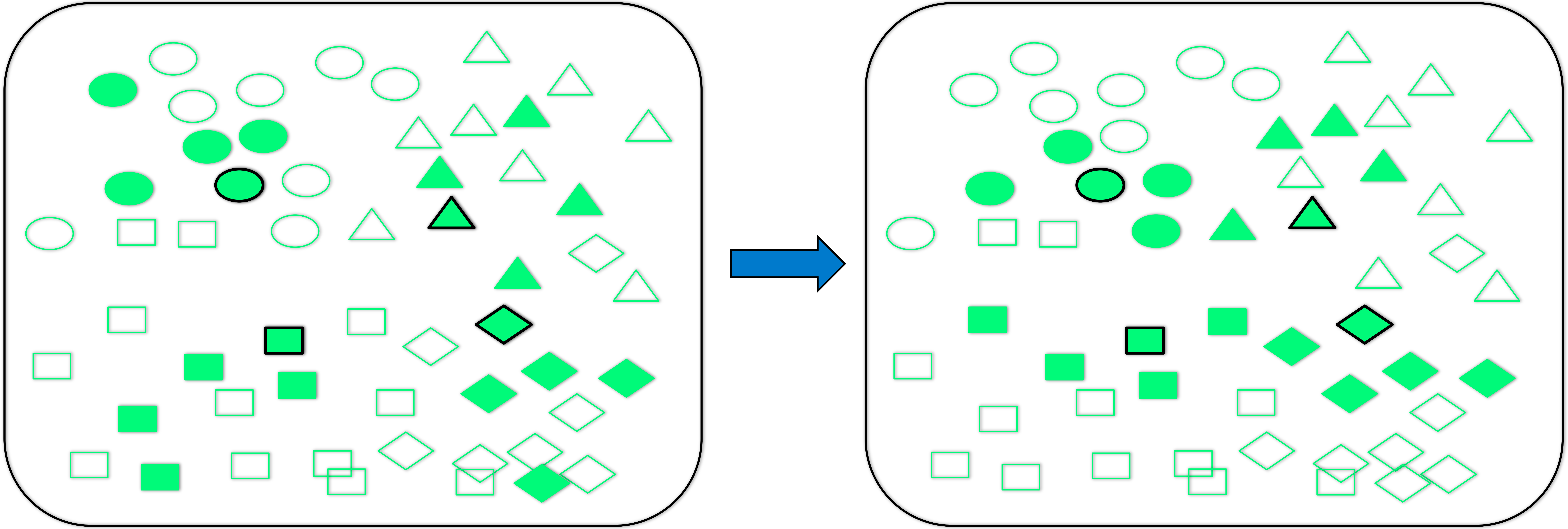
Selections maximize within-cluster similarity only

Representative selection



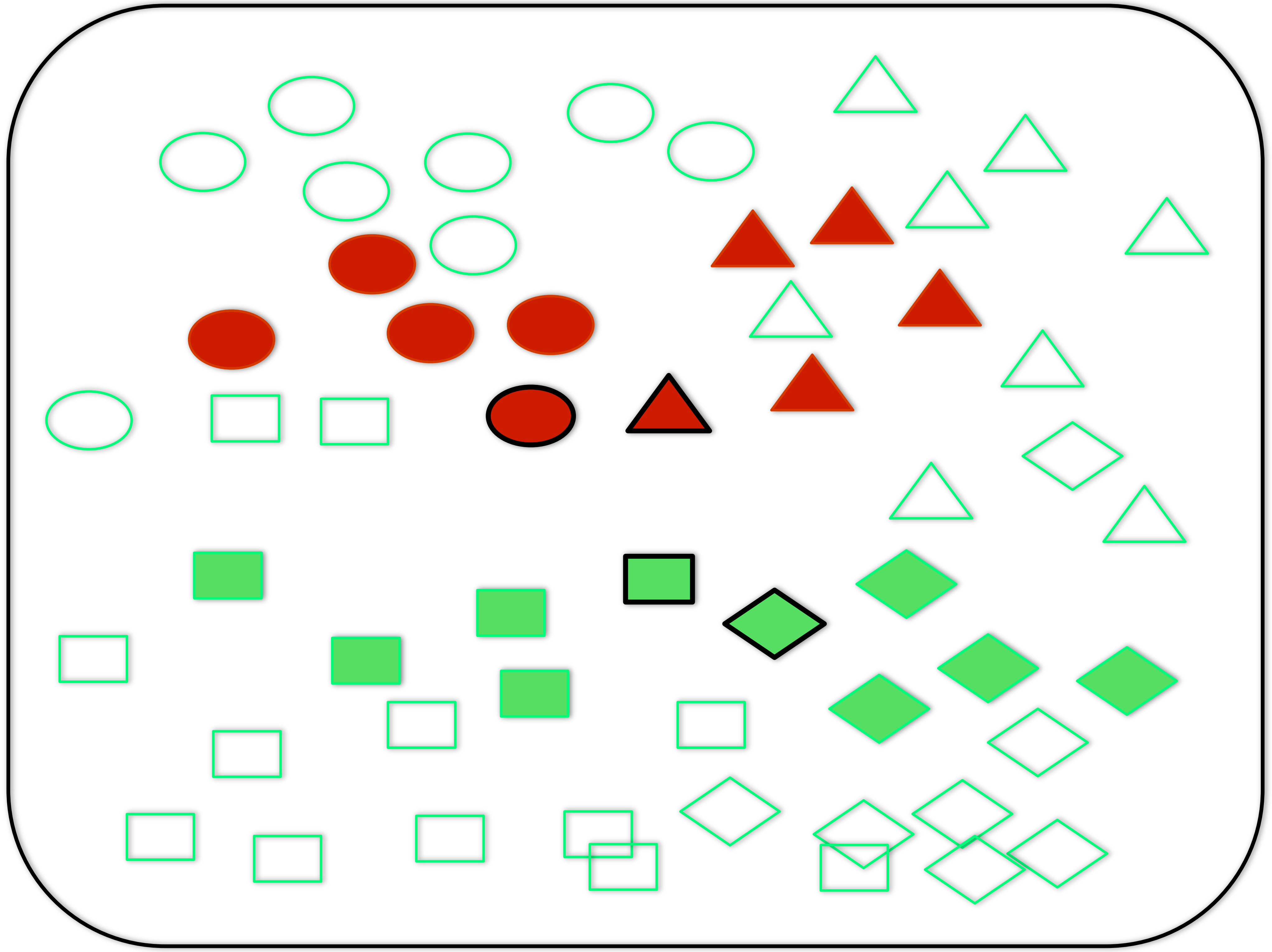
Selections maximize both within- and between-cluster similarity

Resample per-shape hierarchies



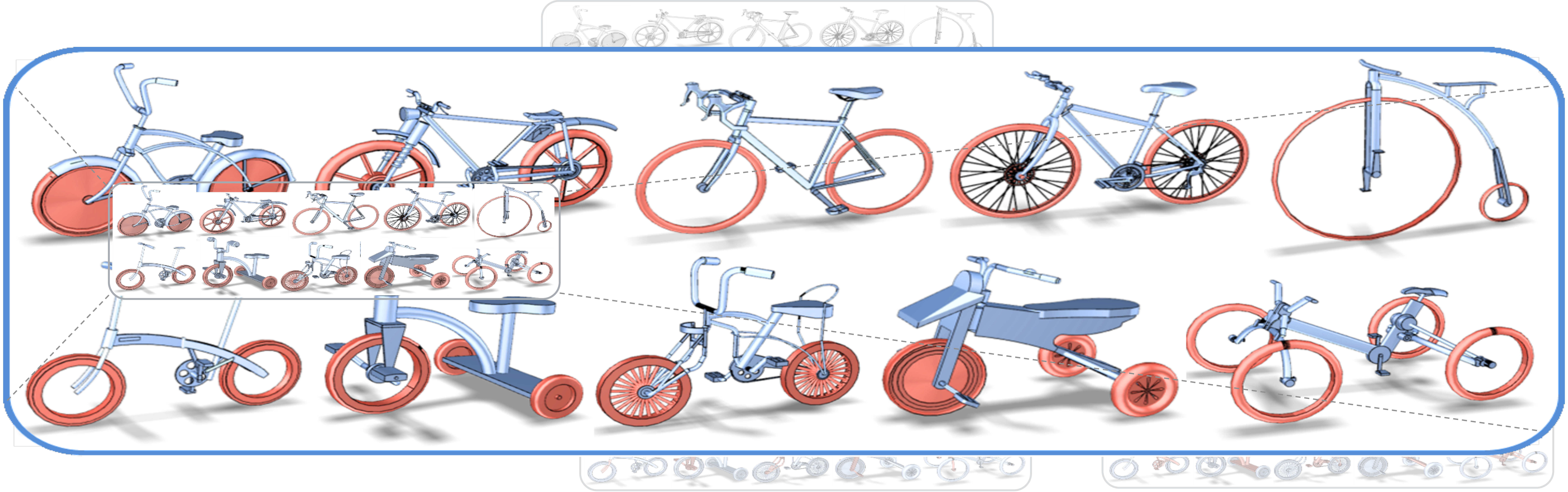
New samples are closer to the representatives

Iterate cluster-select-resample



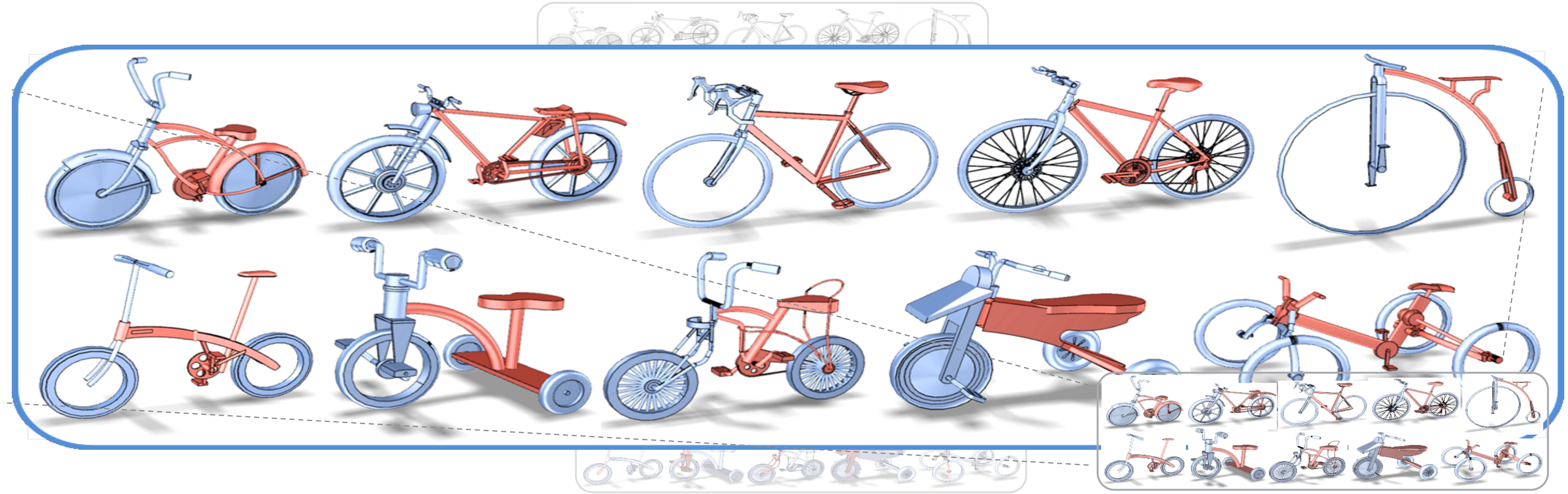
New cluster-select result and repeat until convergence.

Structure correspondence



A co-hierarchy implies correspondence between structures --- towards functional correspondence.

Functional correspondence



A co-hierarchy implies correspondence between structures --- towards functional correspondence.

A short "now and beyond"

- Still most works deal with flat structural organizations
- There is much to be done on hierarchical analysis:
  - All covered techniques are unsupervised
  - How about **supervised:** providing symmetry measures is hard; ground truths for and comparison between hierarchical models are not easy
  - Extension from 3D objects to more complex data, e.g., **indoor scenes**, and mixed object categories

We welcome your feedback!

http://goo.gl/LfVcHA