GRASS: Generative Recursive Autoencoders for Shape Structures

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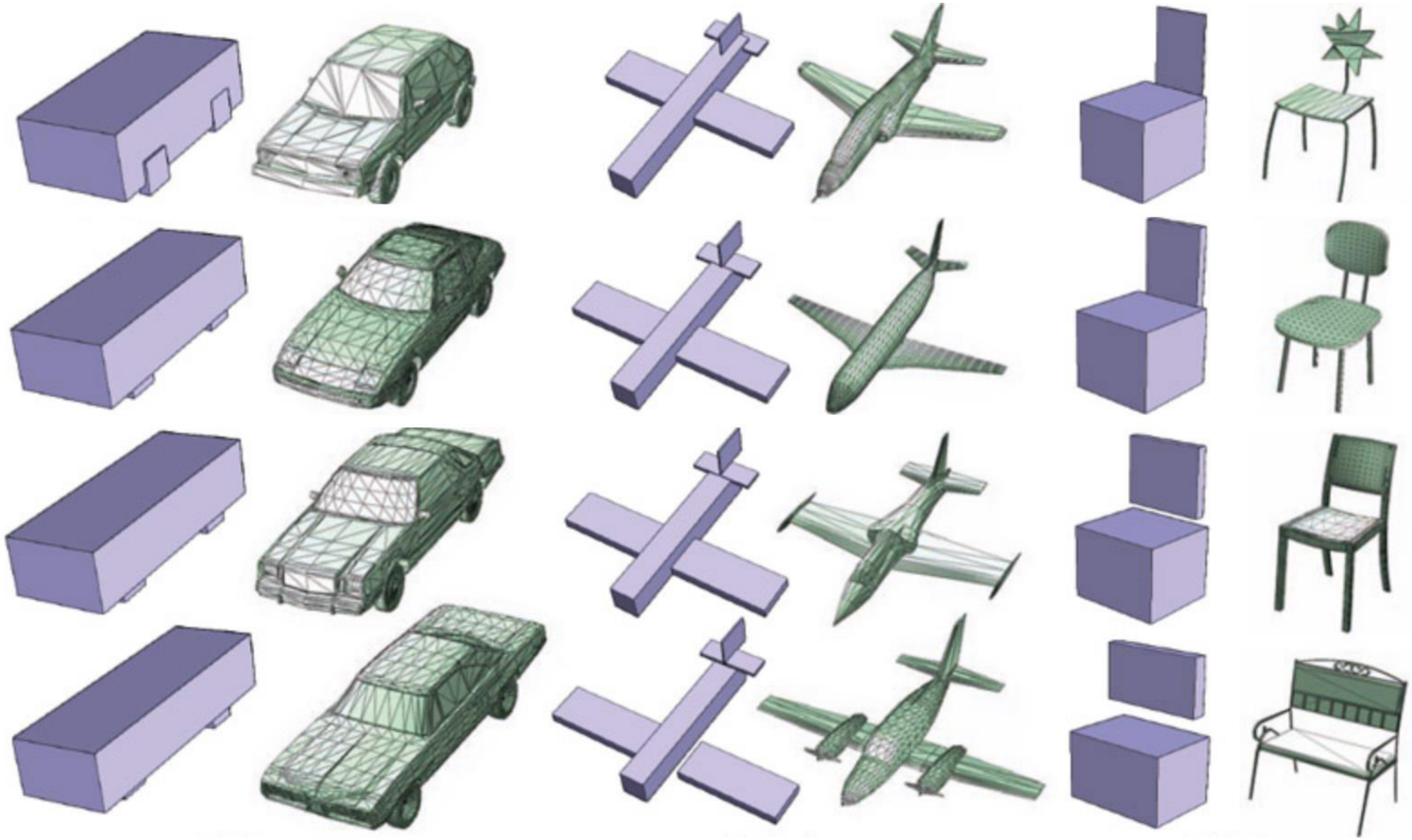
Shapes have different **topologies**

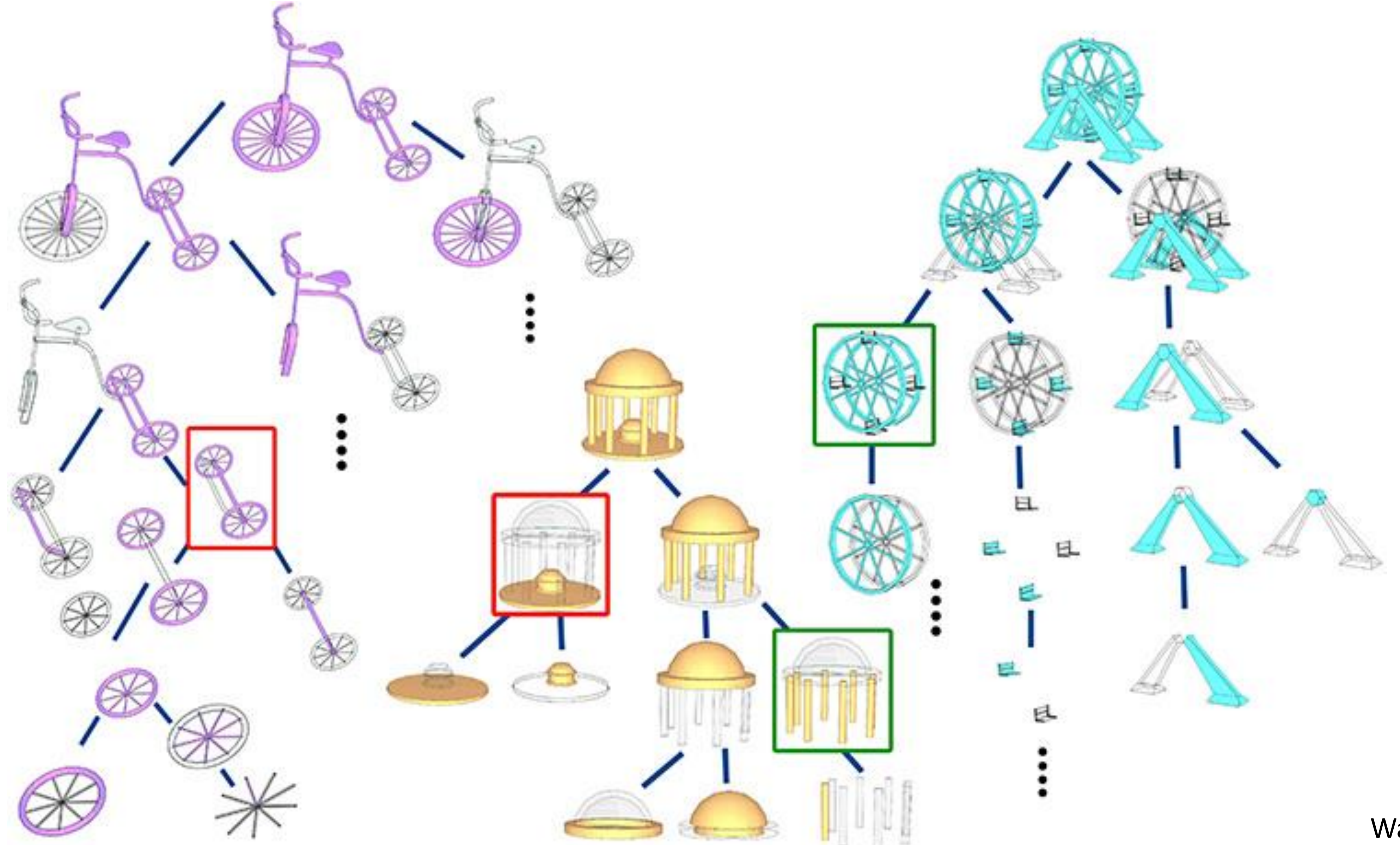
?

Shapes have different **geometries**



Ovsjanikov et al. 2011

Shapes have **hierarchical** compositionality



Wang et al. 2011

Motivating Question

How can we capture

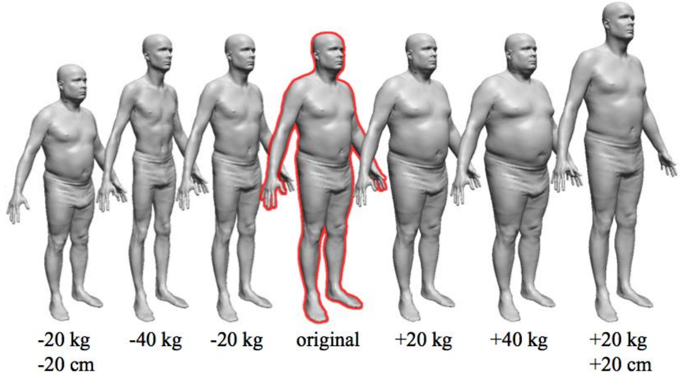
- topological variation
- geometric variation
- hierarchical composition

in a

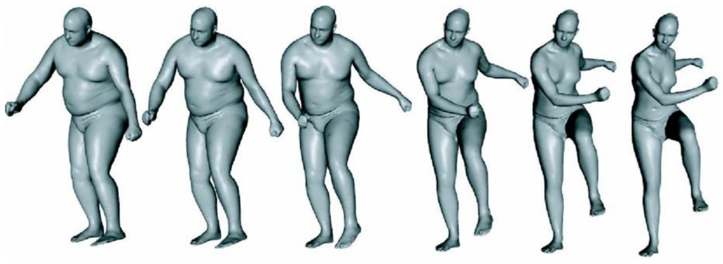
single, generative, fixed-dimensional representation?

Encode ← "Shape DNA" → Generate

Sequences of commands to Maya/AutoCAD

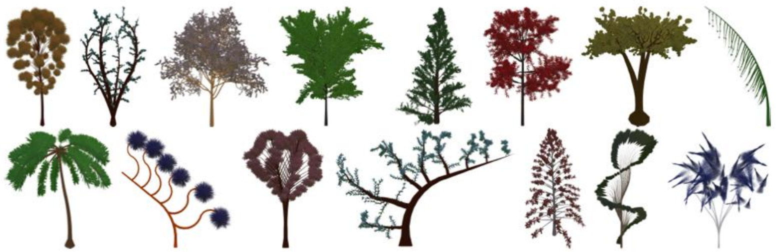


Deformable template [Allen03]

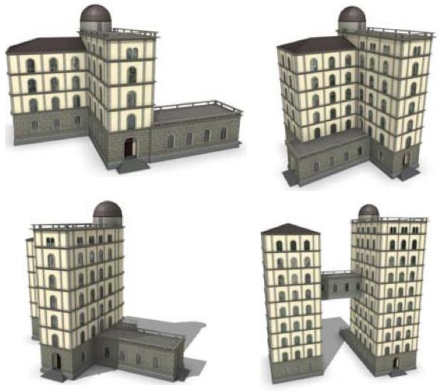


Posed template [Anguelov05]

Parametrized procedure [Weber95]

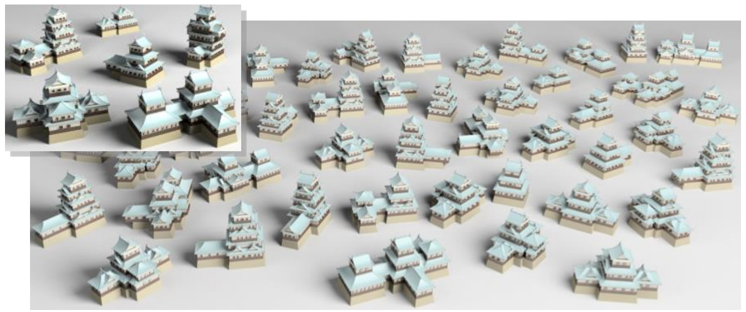


Probabilistic procedure [Talton09]



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

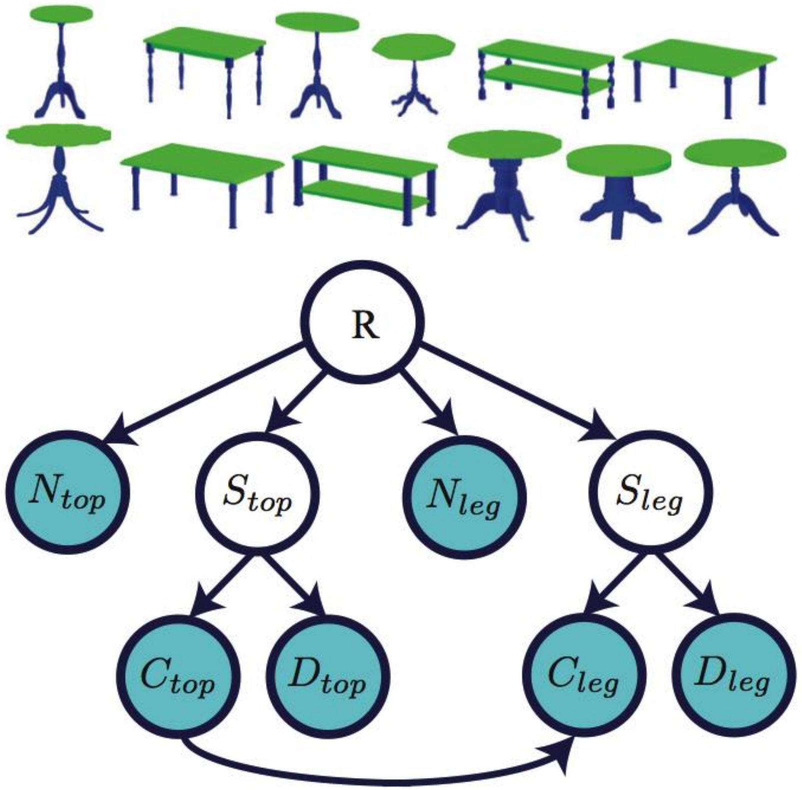
Learned grammar (single exemplar) [Bokeloh10]



Learned grammar (multi-exemplar) [Talton12]

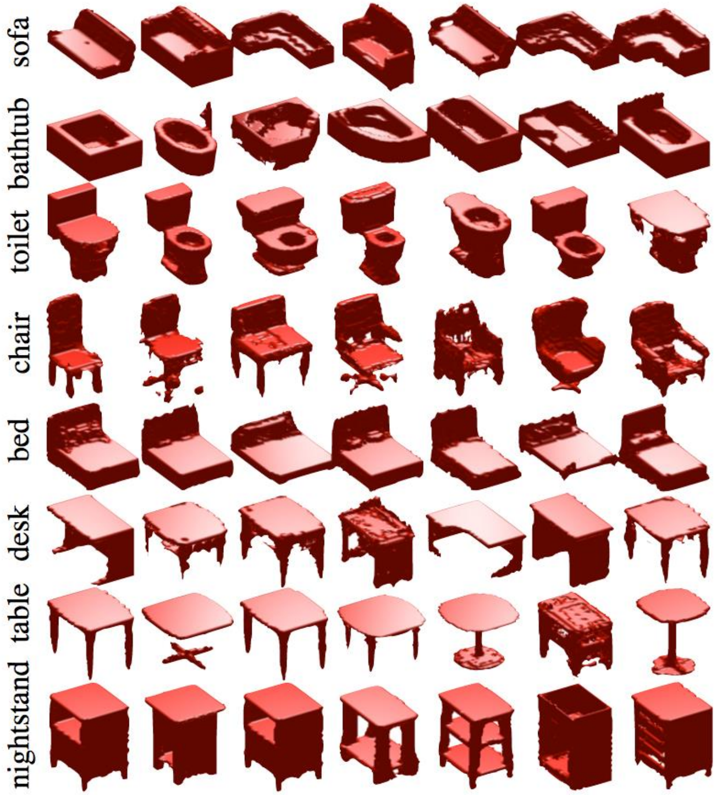
Probabilistic grammar [Müller06]

Structural PGM vs Volumetric DNN



Strongly supervised [Kalogerakis et al. ’12]

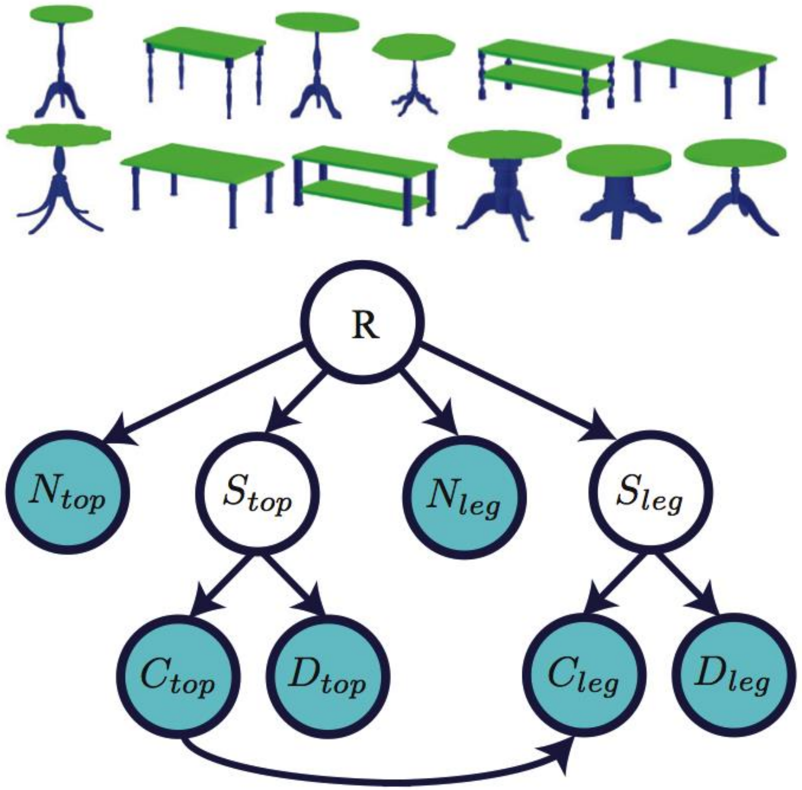
Pros: direct model of compositional structure, (relatively) low-dimensional, high quality output
Cons: limited topological variation, no continuous geometric variation (for generation), no hierarchy, huge effort to segment & label training data



Unsupervised [Wu et al. ’15]

Pros: arbitrary geometry/topology, unsupervised
Cons: low-resolution, no explicit separation of structure vs fine geometry, no guarantee of symmetry/adjacency, no hierarchy, lots of parameters, lots of training data

Structural PGM vs Volumetric DNN



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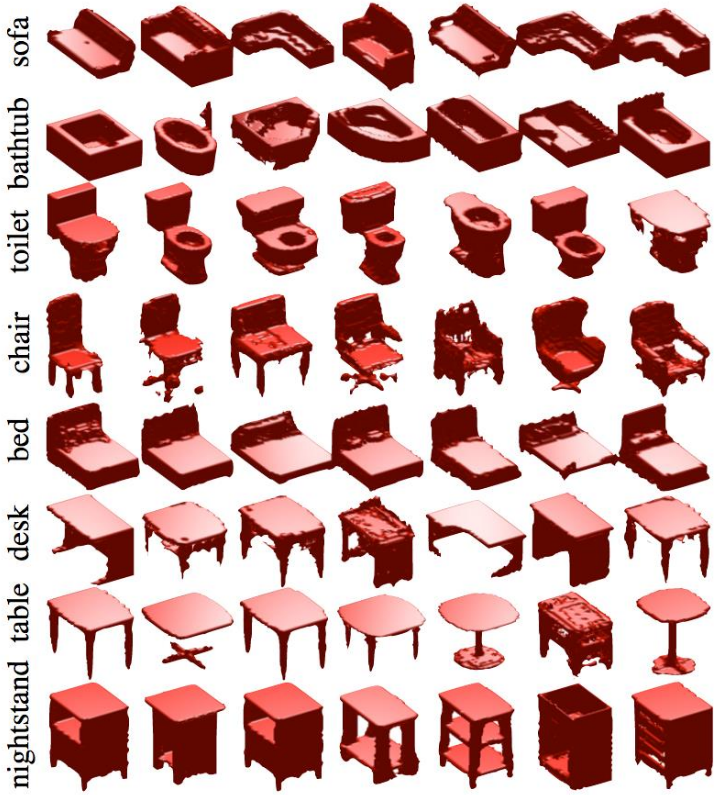

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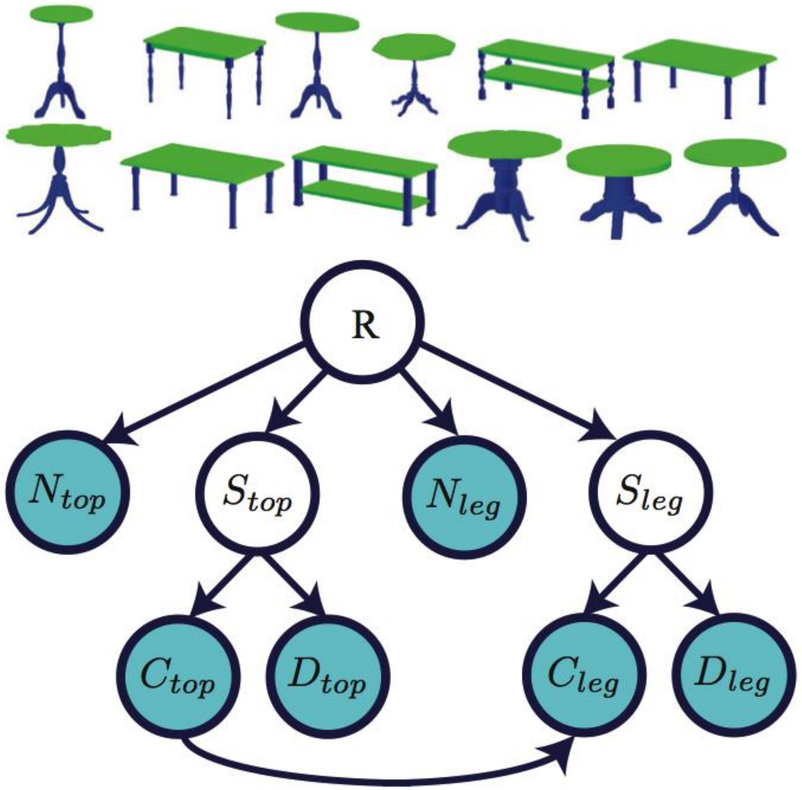

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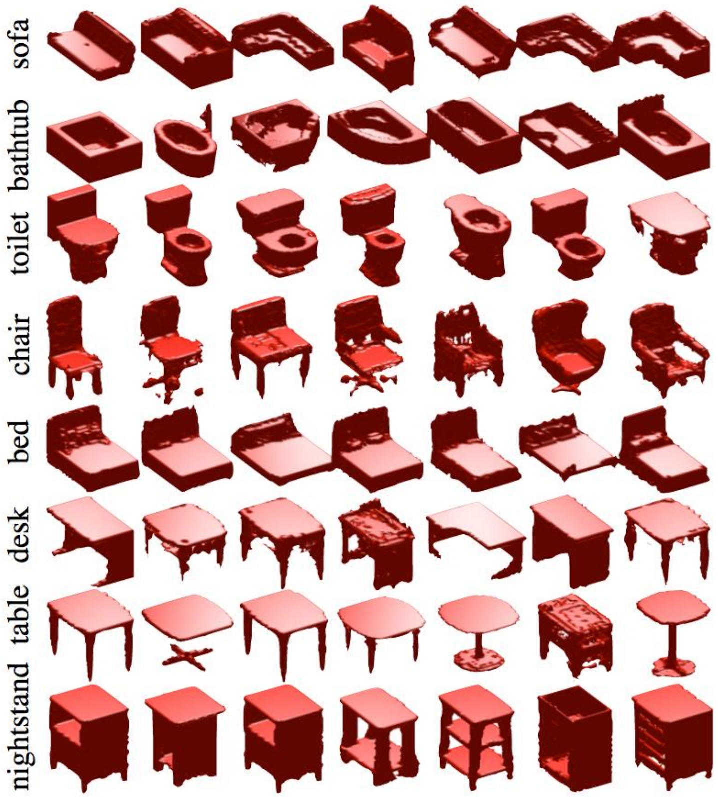

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GRASS: Generative neural networks over unlabeled part layouts

- GRASS factorizes a shape into a hierarchical layout of simplified parts, plus fine-grained part geometries
- Weakly supervised:
  - ✓ segments
  - ✗ labels
  - ✗ manually-specified “ground truth” hierarchies
- Structure-aware: learns a generative distribution over richly informative structures

Three Challenges

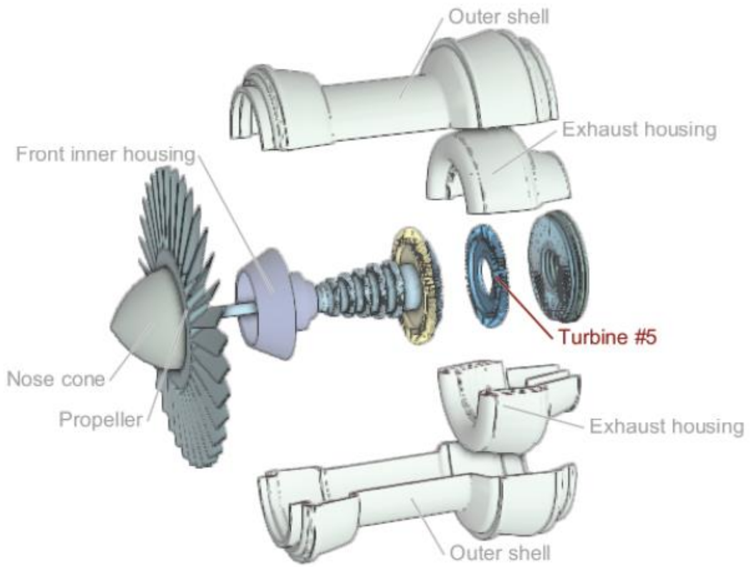
- **Challenge 1:** Ingest and generate arbitrary part layouts with a fixed-dimensional network
  - Convolution doesn't work over arbitrary graphs

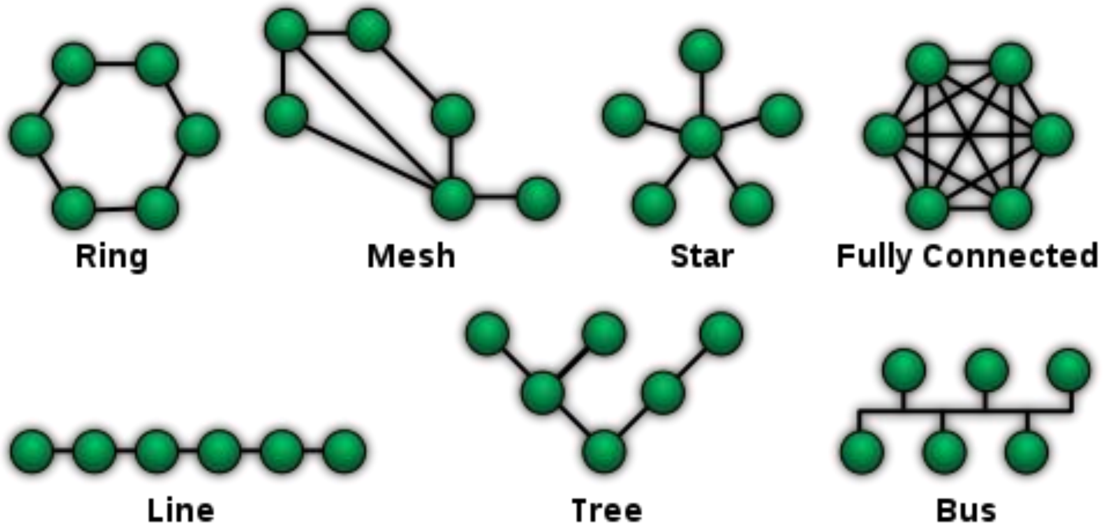
- **Challenge 2:** Map a layout invertibly to a fixed-D code ("Shape DNA") that implicitly captures adjacency, symmetry and hierarchy

- **Challenge 3:** Map layout features to fine geometry

Huge variety of (attributed) graphs

- Arbitrary numbers/types of vertices (parts), arbitrary numbers of connections (adjacencies/symmetries)



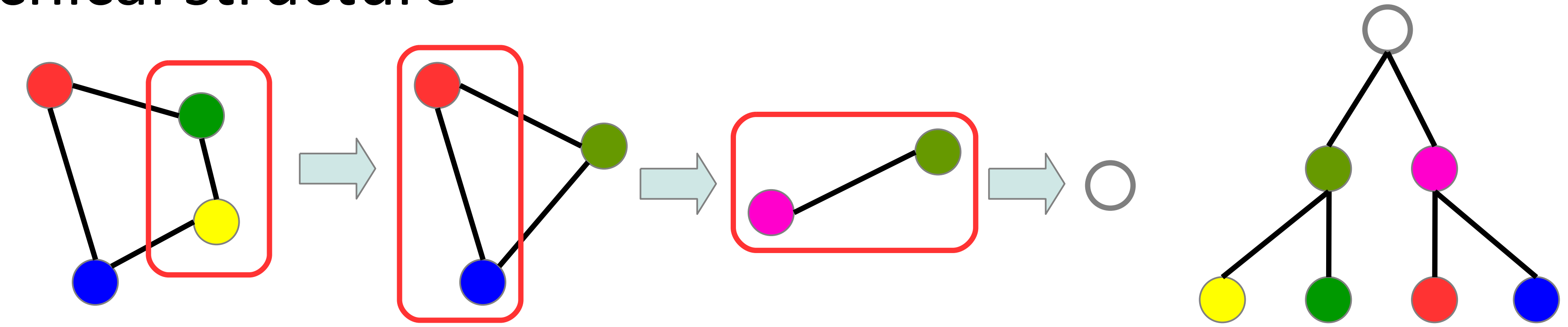


- For linear graphs (chains) of arbitrary length, we can use a recurrent neural network (RNN/LSTM)

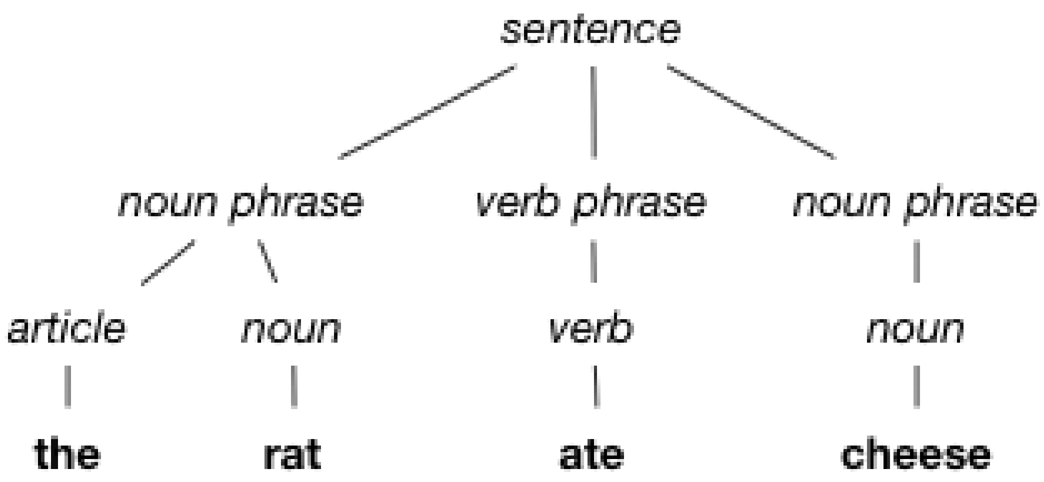
Li et al. 2008, Wikipedia

Key Insight

- Edges of a graph can be collapsed sequentially to yield a hierarchical structure

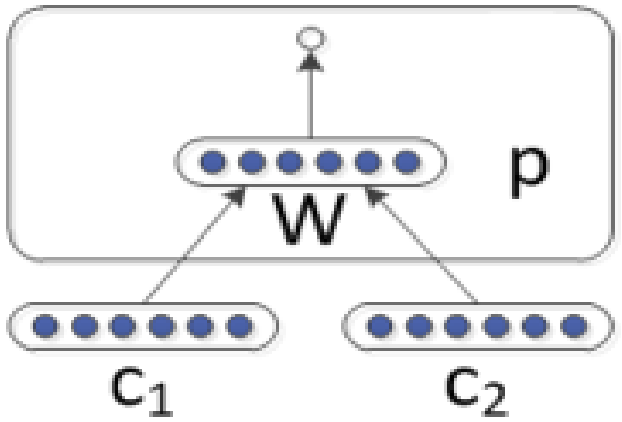


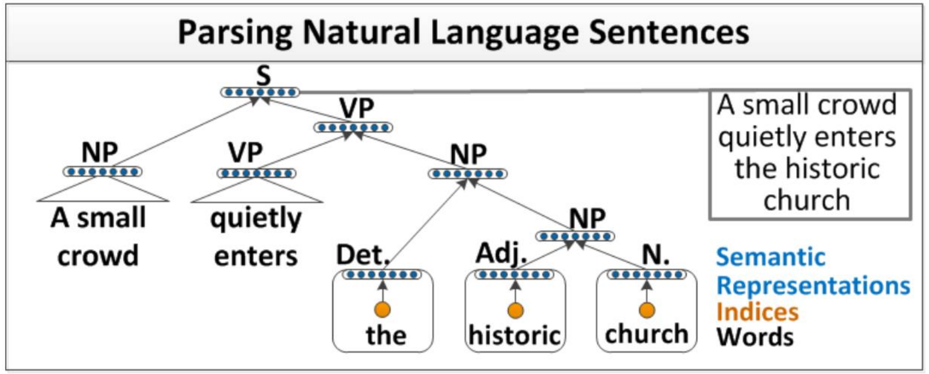
- Looks like a parse tree for a sentence!
- … and there are unsupervised sentence parsers

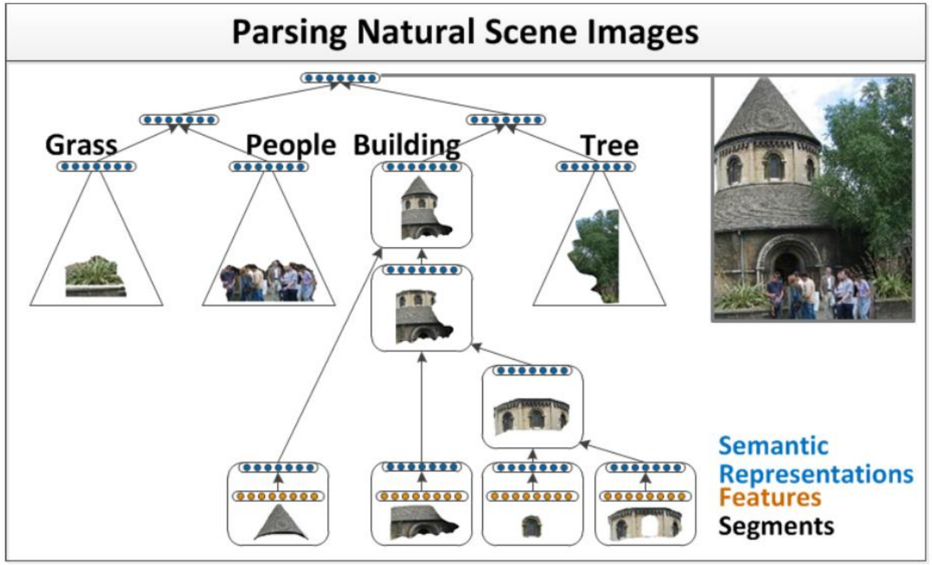


Recursive Neural Network (RvNN)

- Repeatedly merge two nodes into one
- Each node has an n-D feature vector, computed recursively
- $p = f(W[c_1; c_2] + b)$

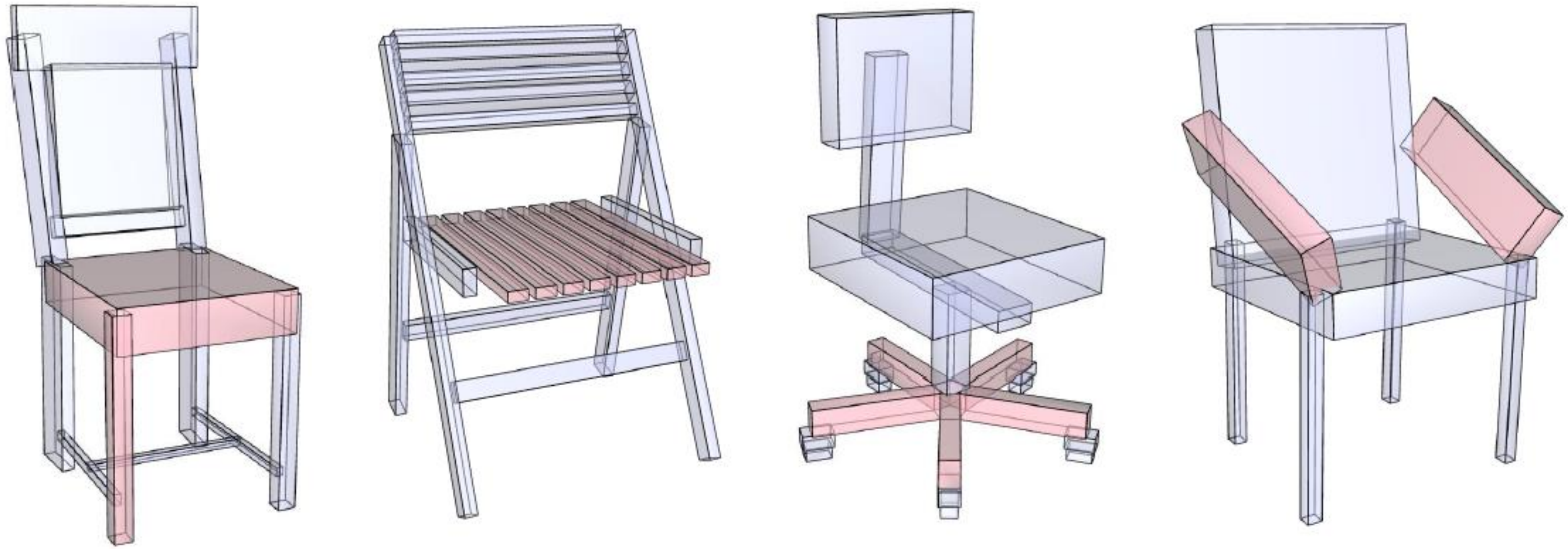






Socher et al. 2011

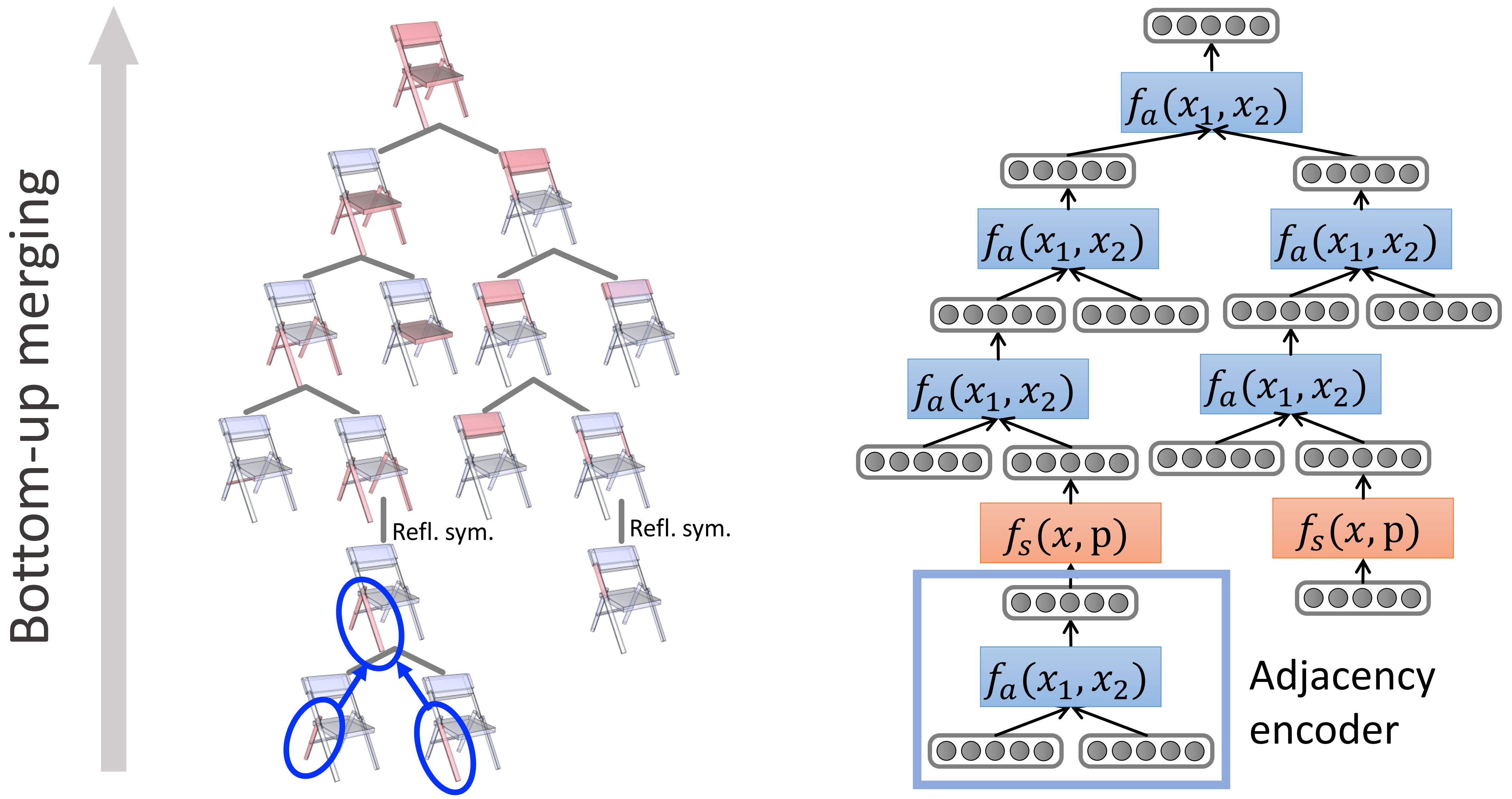
Different types of merges, varying cardinalities!



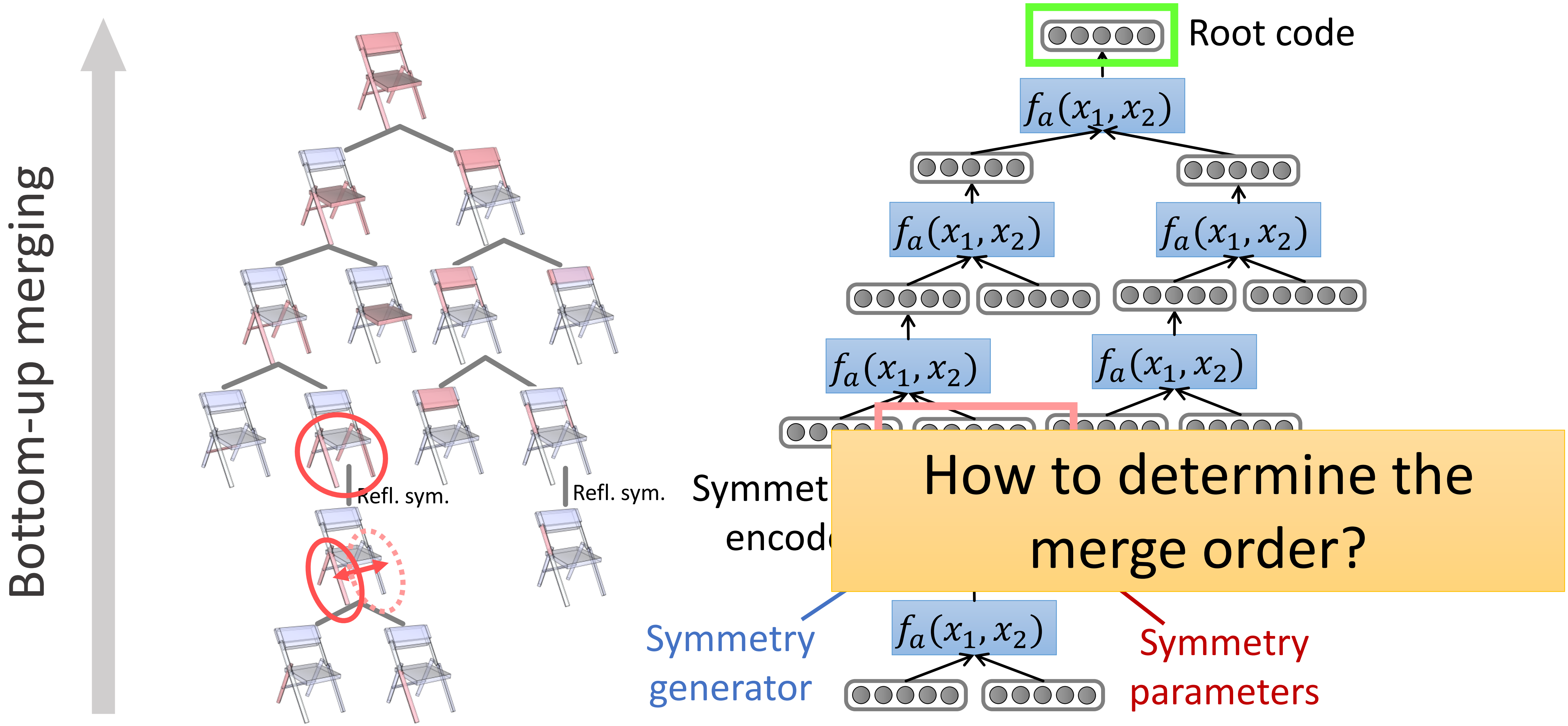
Adjacency | Translational symmetry | Rotational symmetry | Reflectional symmetry

- How to encode them to the same code space?
- How to decode them appropriately, given just a code?

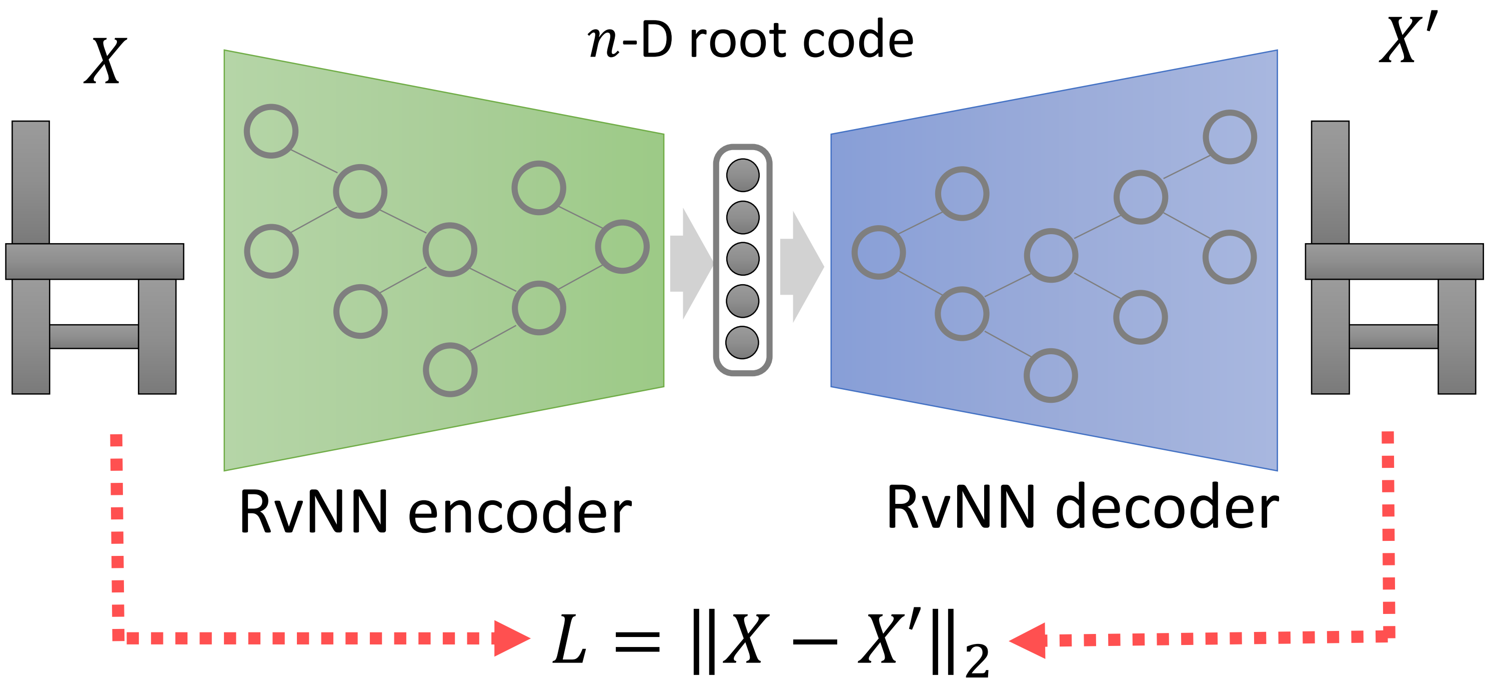
Recursively merging parts



Recursively merging parts



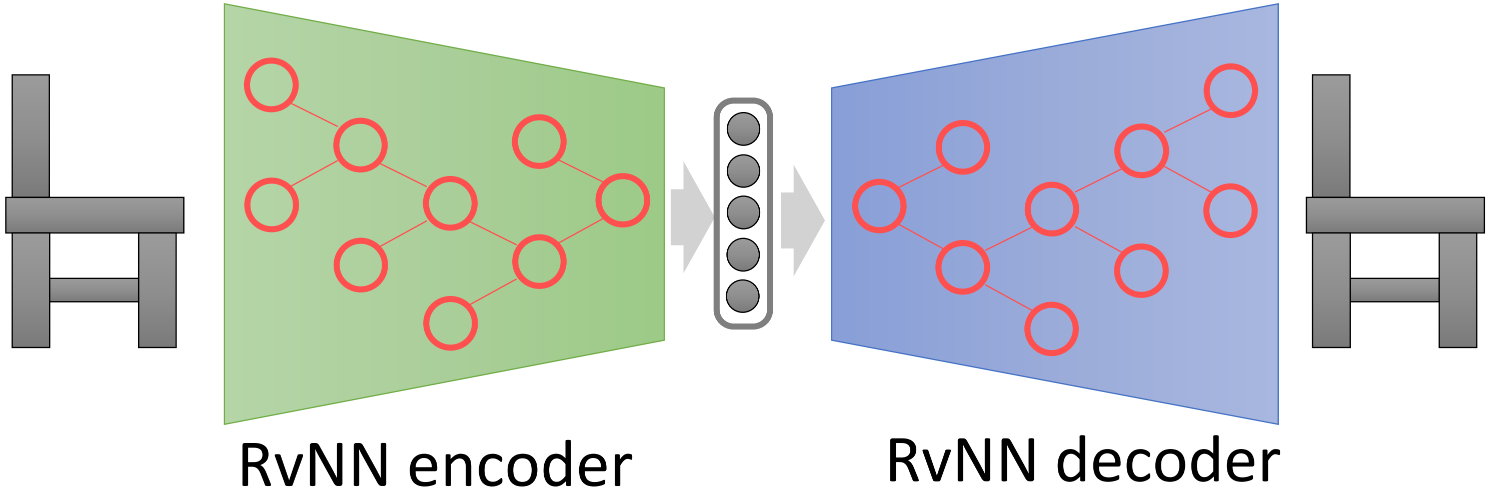
Training with reconstruction loss



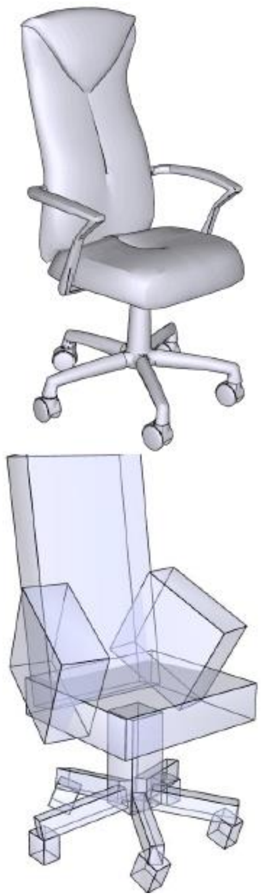
- Learn weights from a variety of randomly sampled merge orders for each box structure

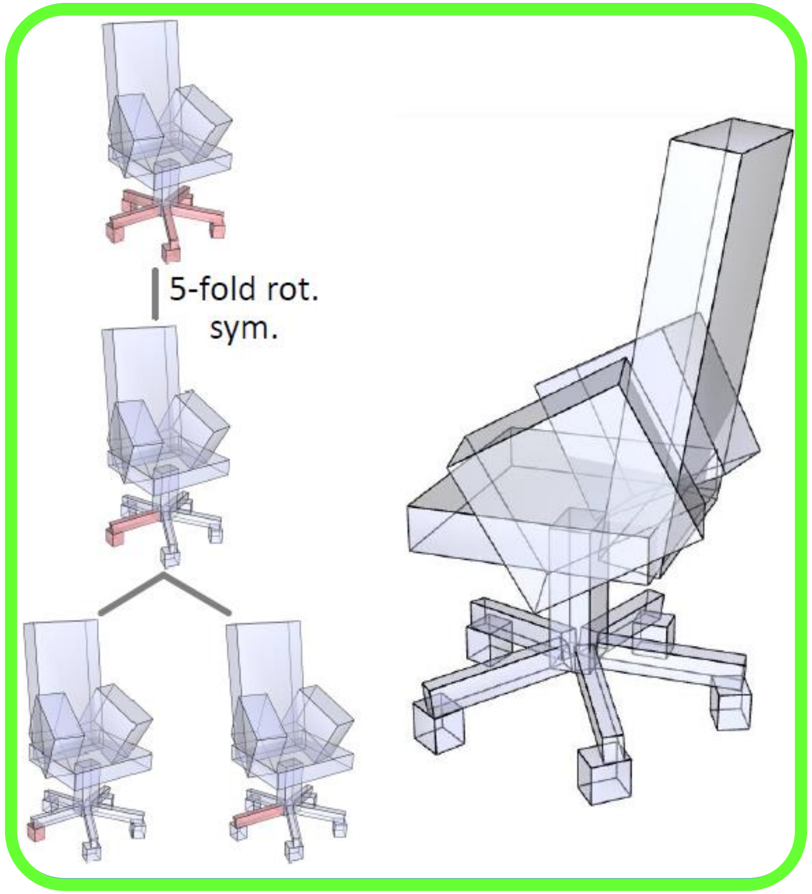
In **testing**

- Encoding: Given a box structure, determine the merge order as:
  - The hierarchy that gives the lowest reconstruction error

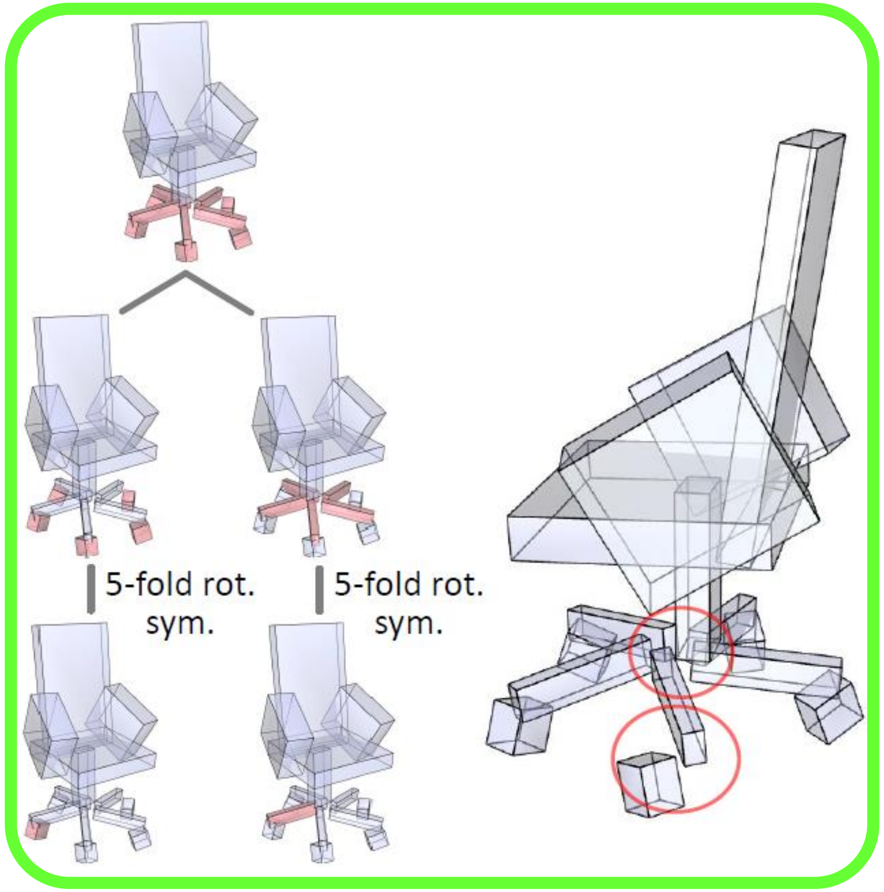


Inferring symmetry hierarchical reconstruction loss





Low reconstruction loss

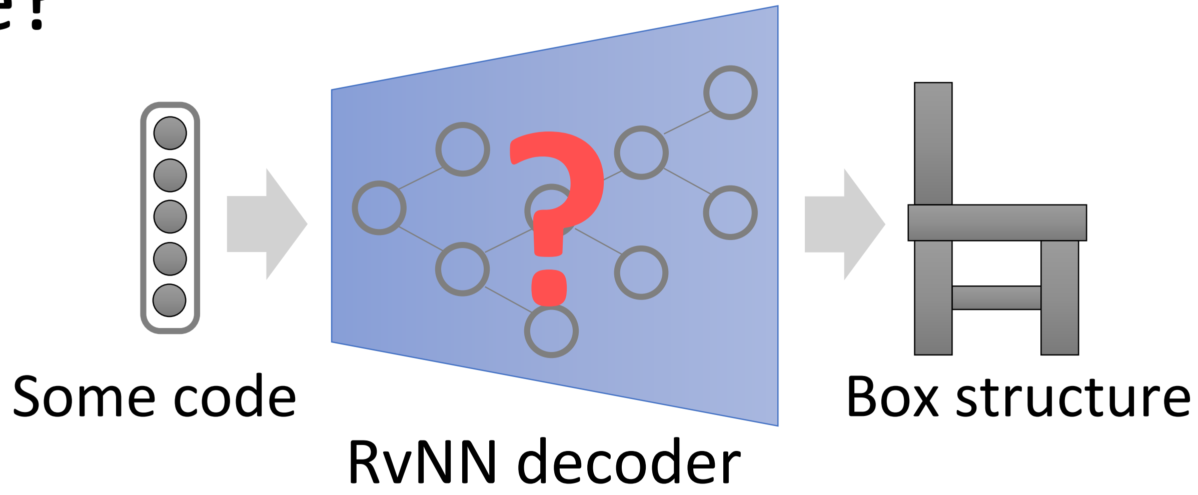


High reconstruction loss

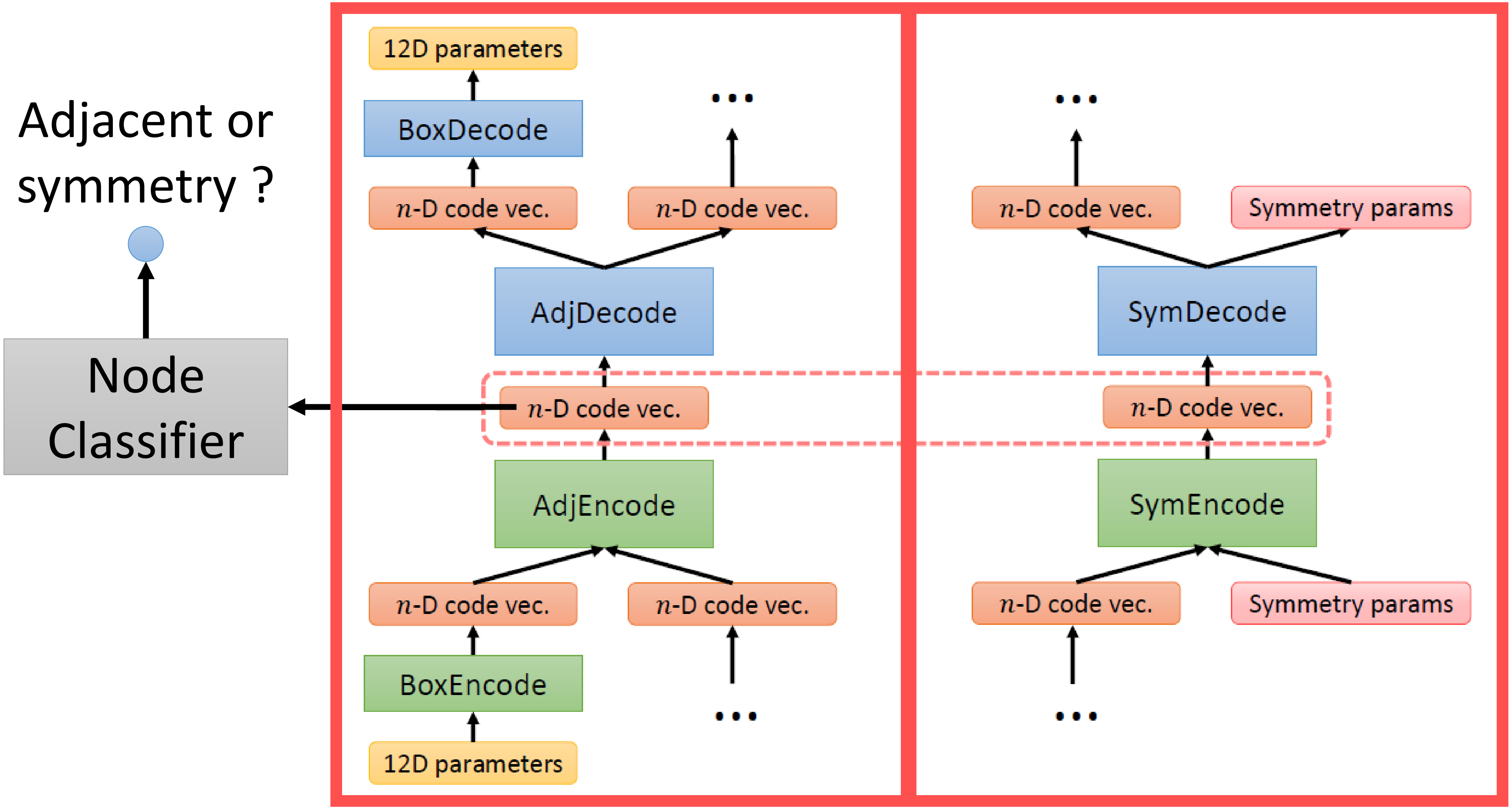
In **testing**

- Encoding: Given a box structure, determine the merge order as:
  - The hierarchy that gives the lowest reconstruction error

- Decoding: Given an arbitrary code, how to generate the corresponding structure?



How to know what type of encoder to use?



Making the network generative

- Variational Auto-Encoder (VAE): Learn a distribution that approximates the data distribution of true 3D structures

$$P(X) \approx P_{gt}(X)$$

- Marginalize over a latent “DNA” code

$$\text{maximize } P(X) = \int \underbrace{P(X|z;\underbrace{\theta}_{\text{Parameters}})}_{\text{Likelihood}} P(z)\,dz$$

Variational Bayes formulation

maximize $P(X) = \int P(X|z;\theta)P(z)dz$

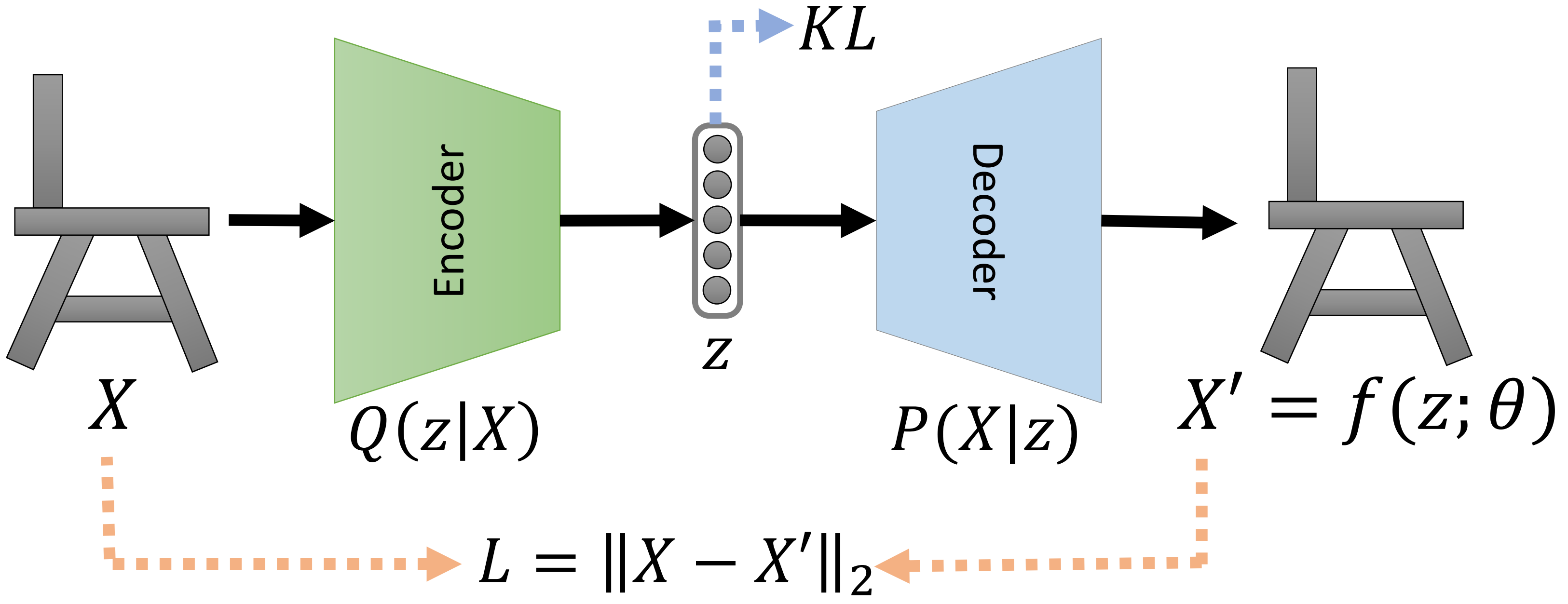
maximize $\boxed{E_{z\sim Q}[\log P(X|z)]} - \boxed{\mathcal{D}[Q(z|X)\|P(z)]}$

z should reconstruct X, given that it was drawn from $Q(z|X)$

Assuming z's follow a normal distribution

Variational Autoencoder (VAE)

maximize $\underbrace{\boxed{E_{z\sim Q}\left[\log P(X|z)\right]}}_{\text{Reconstruction loss}} - \underbrace{\boxed{\mathcal{D}\left[Q(z|X)\|P(z)\right]}}_{\text{KL divergence loss}}$



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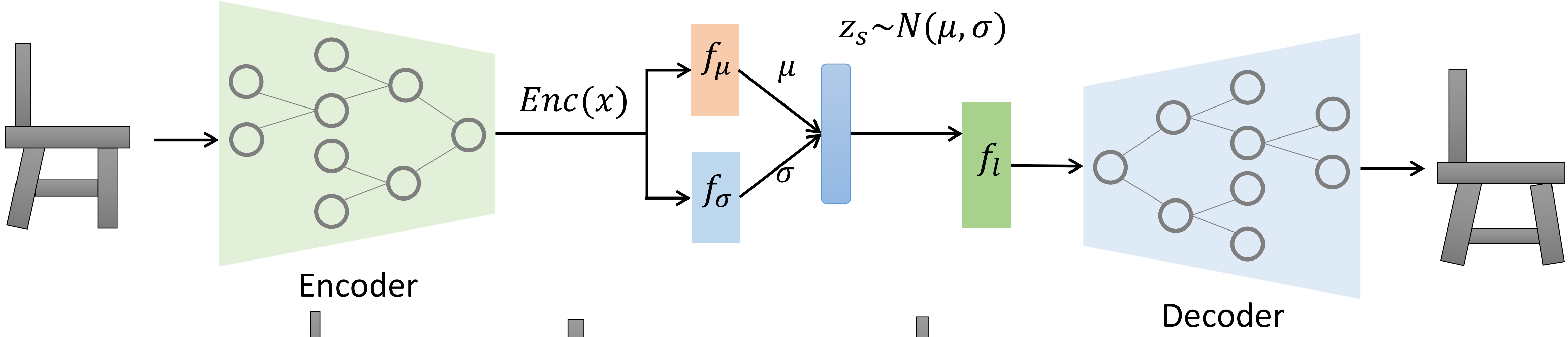
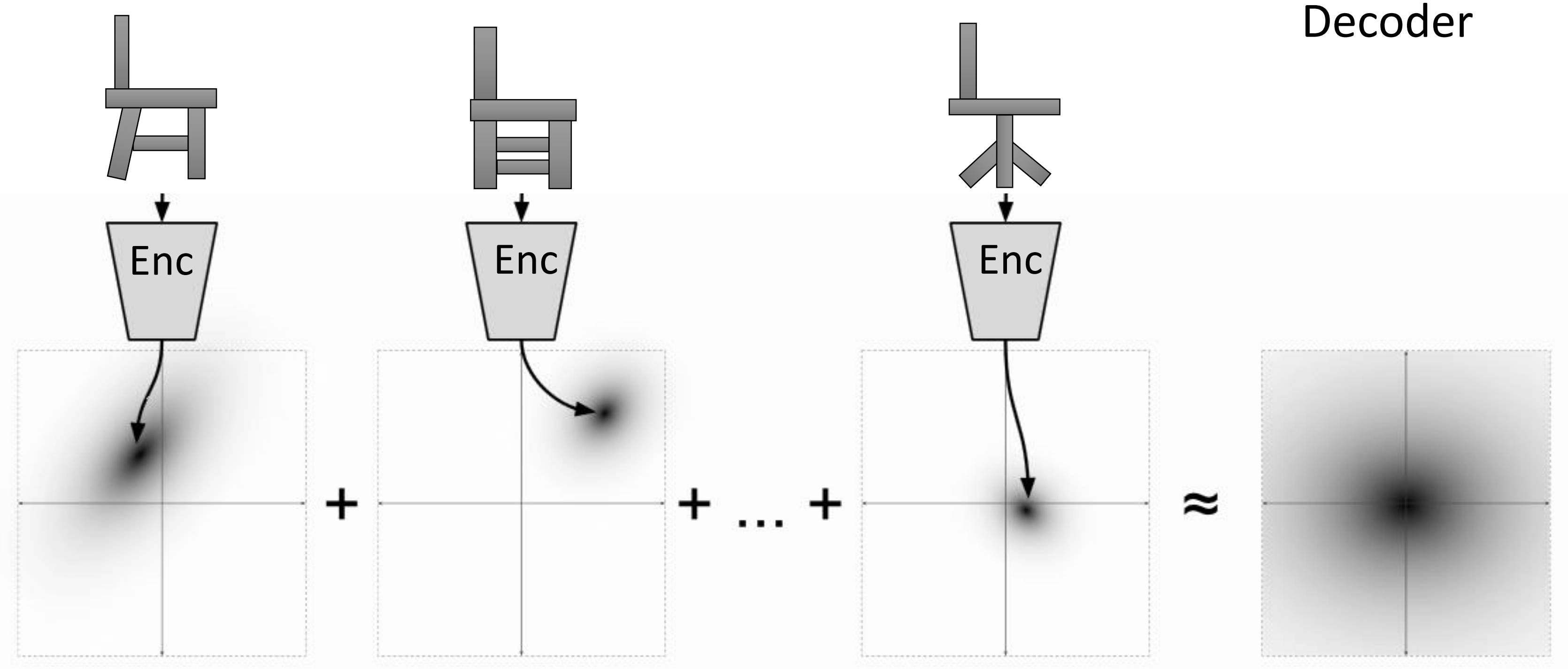
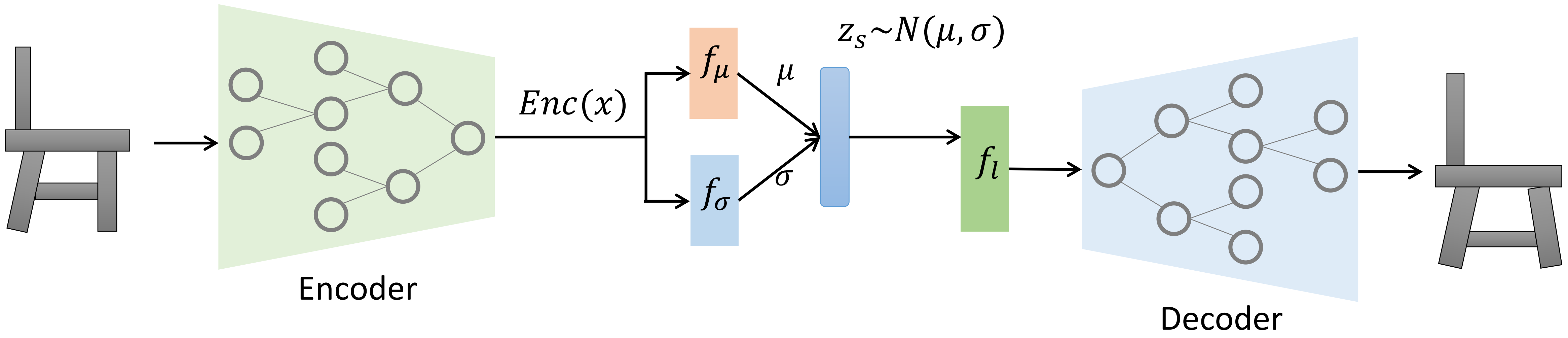
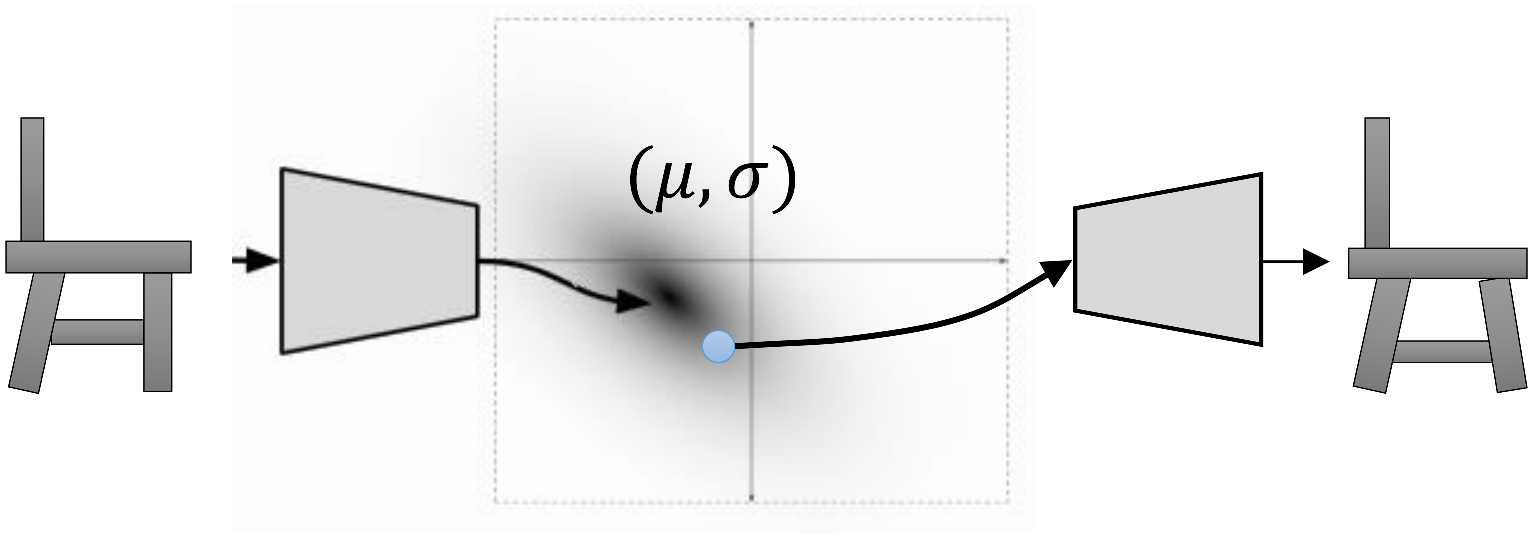


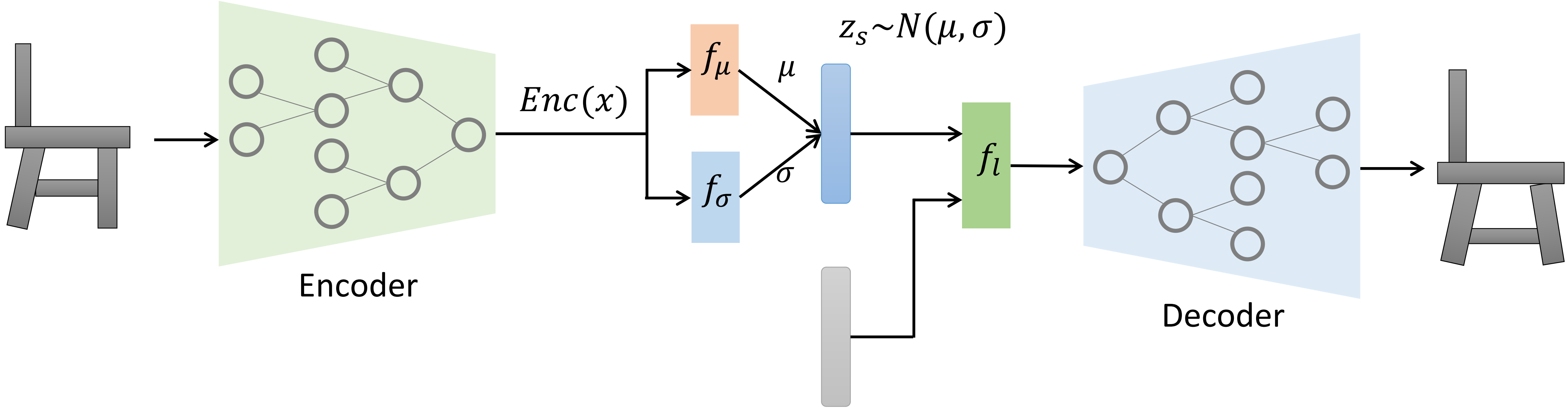


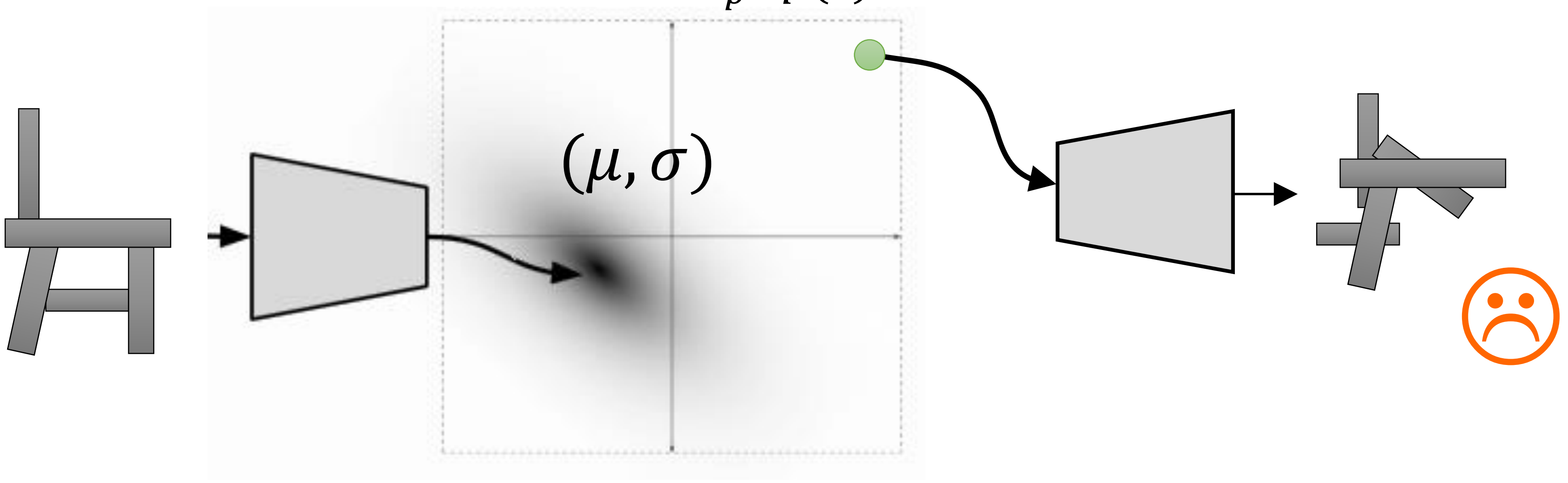
Sampling near μ is robust



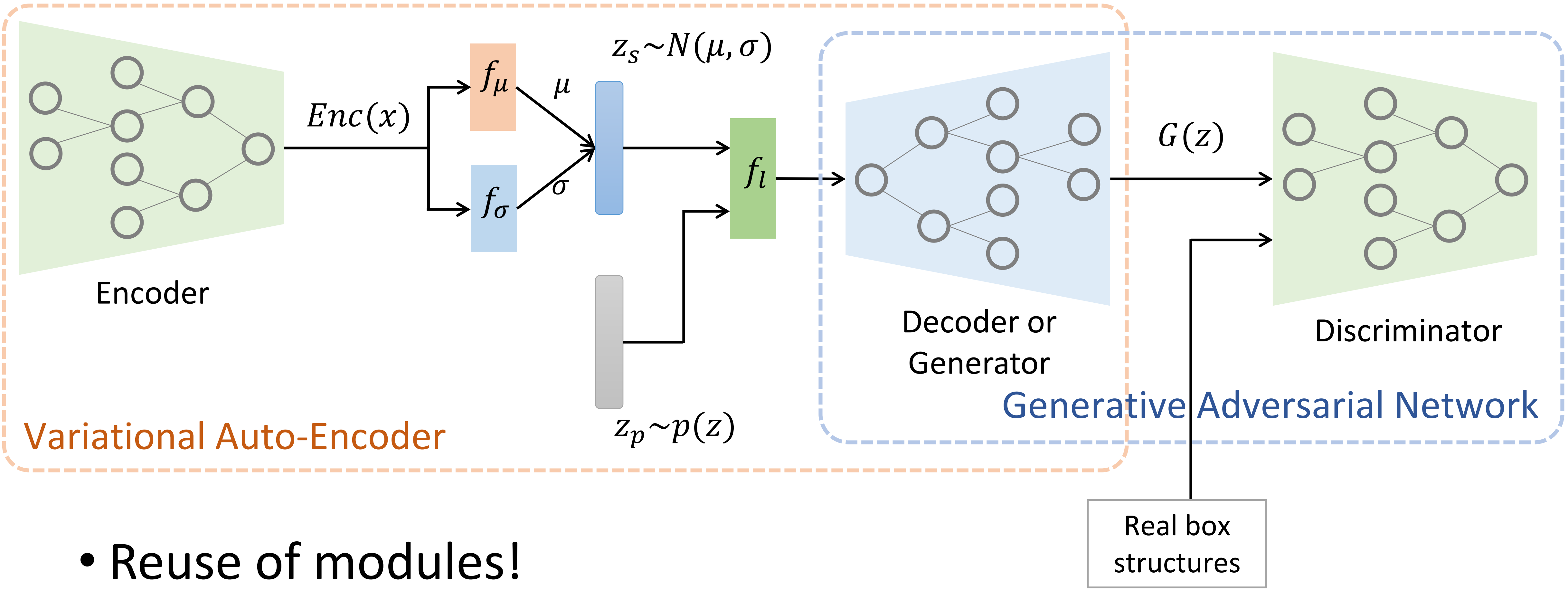


Sampling far away from μ?



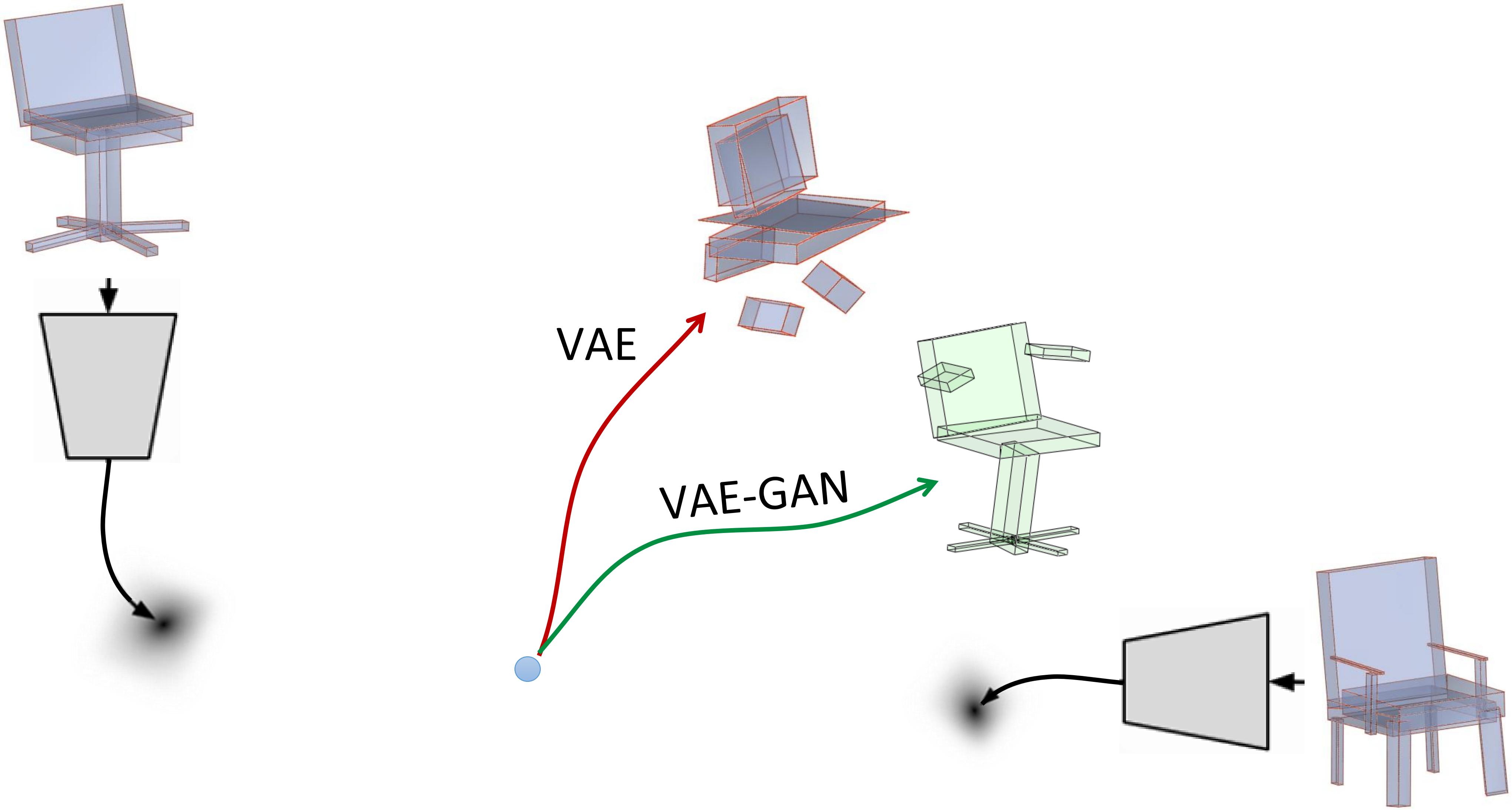


Adversarial training: VAE-GAN

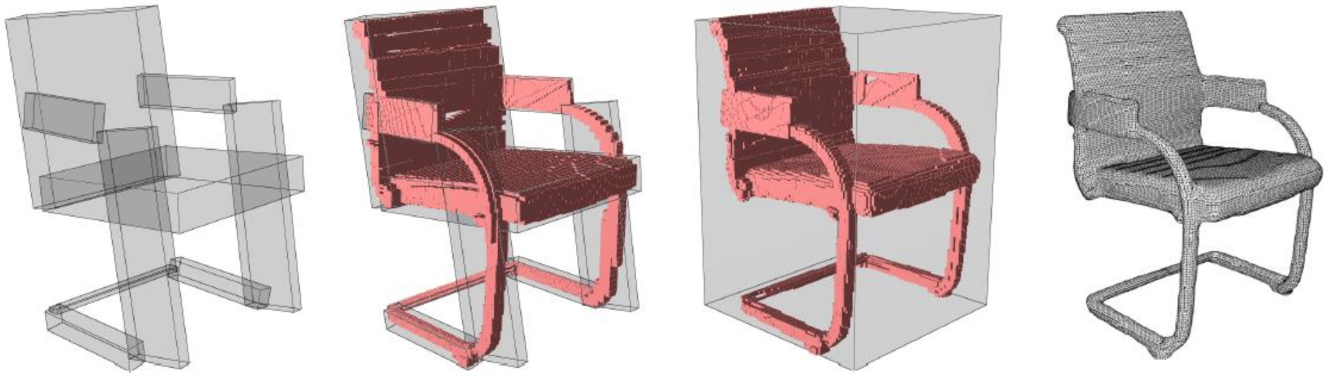


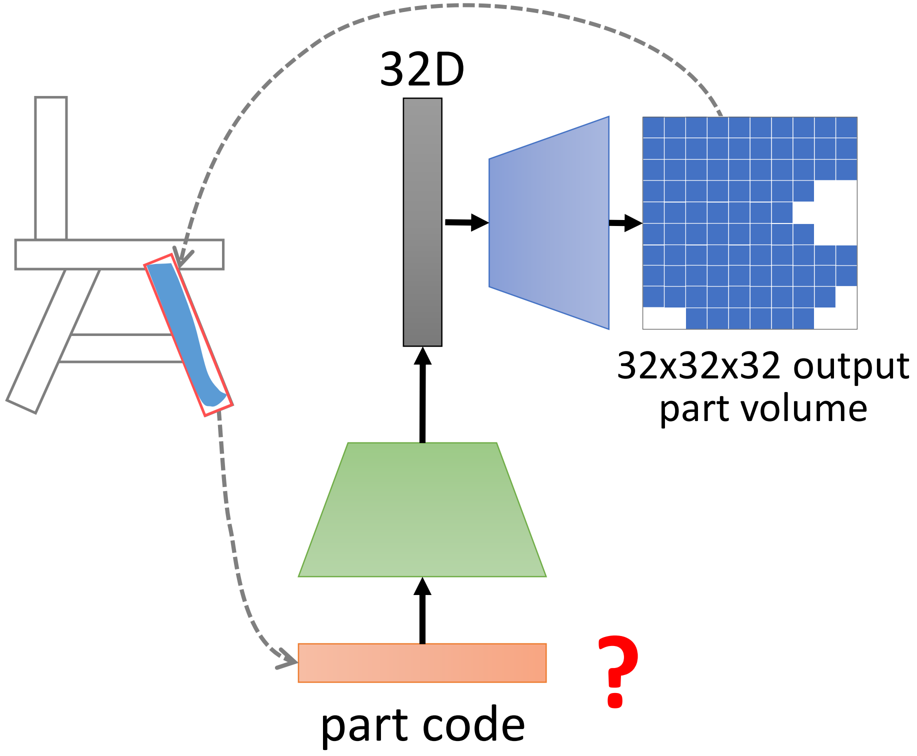
- Reuse of modules!
  - VAE decoder → GAN generator
  - VAE encoder → GAN discriminator

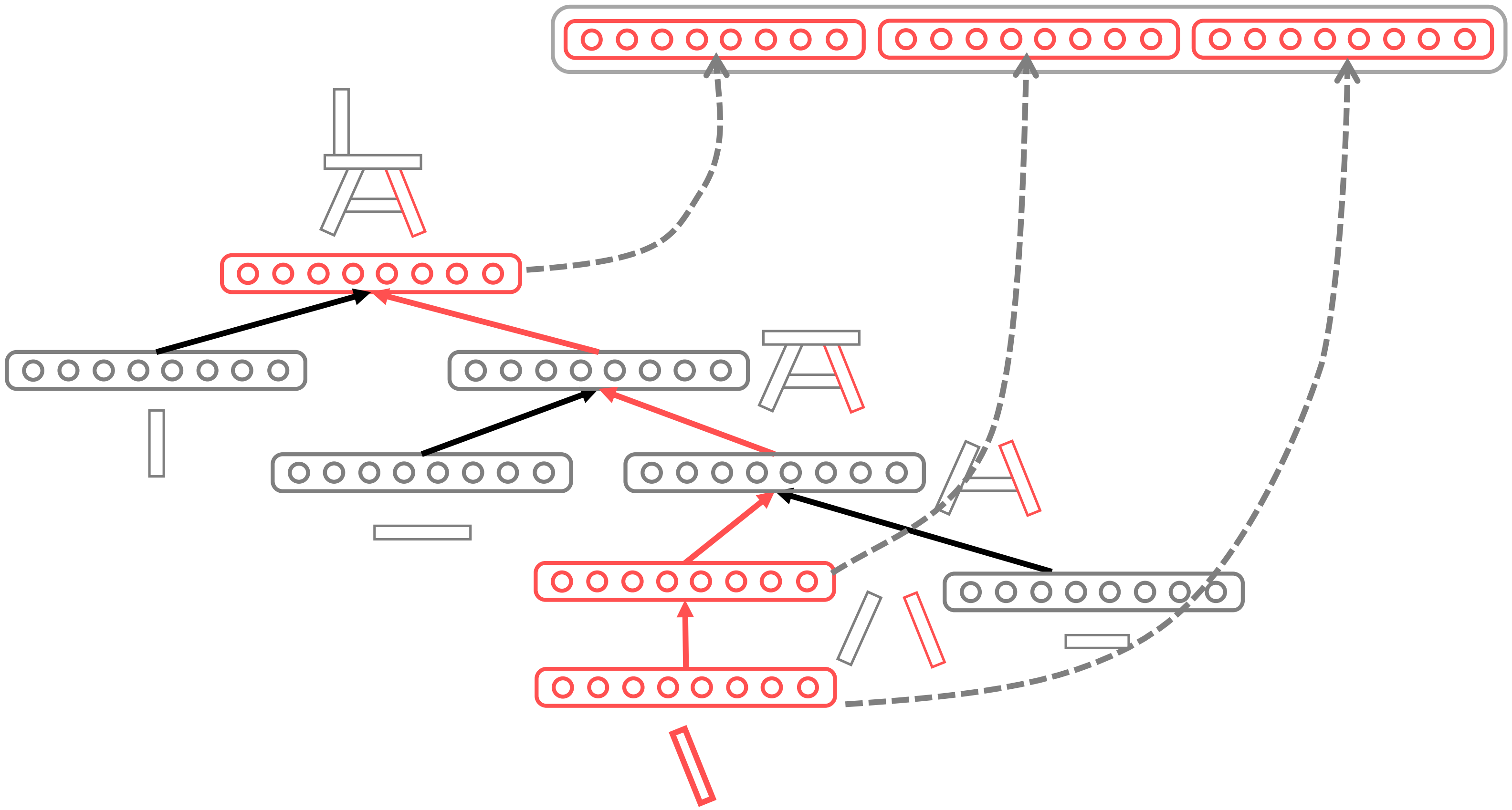
Benefit of adversarial training



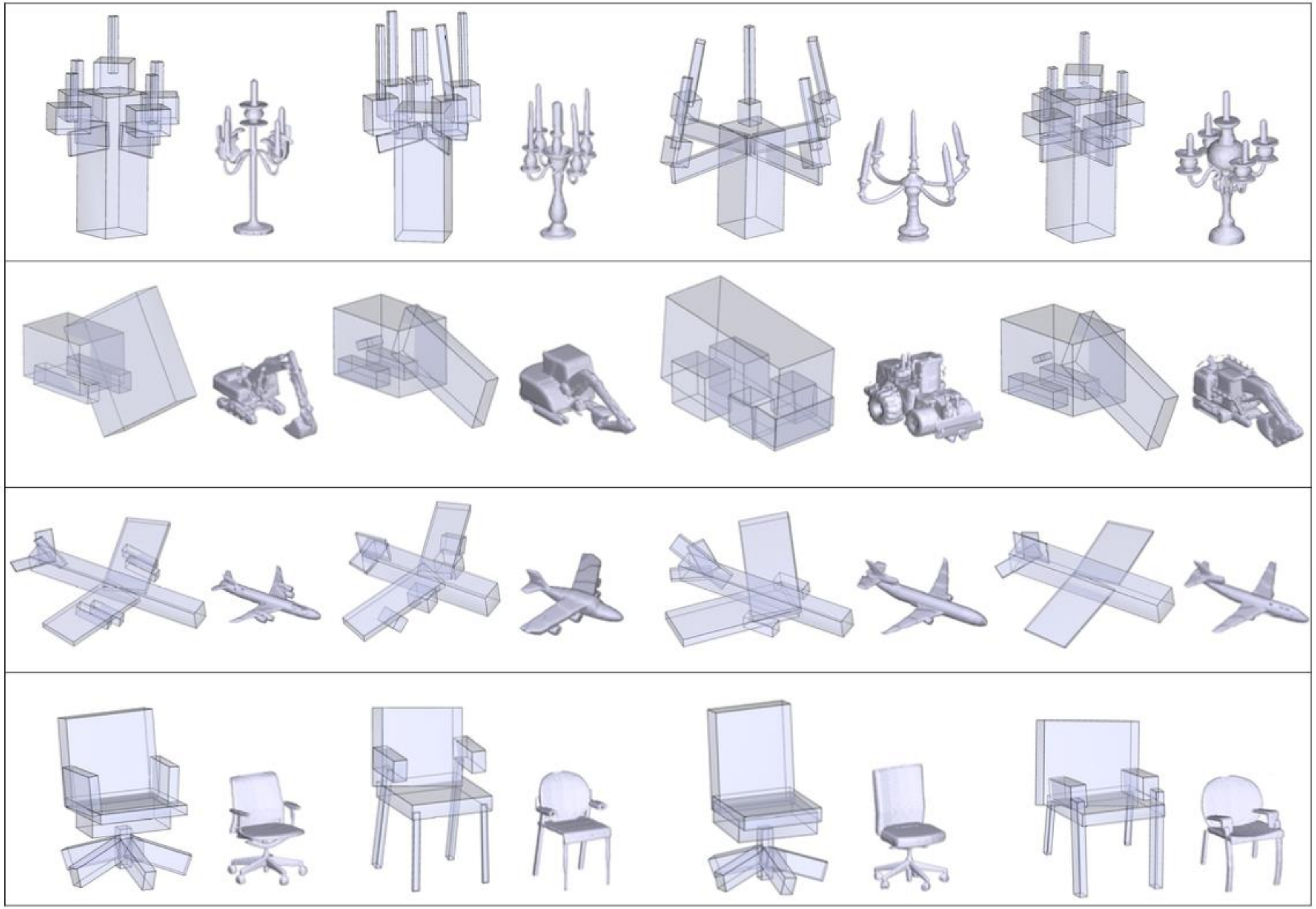
Part geometry synthesis



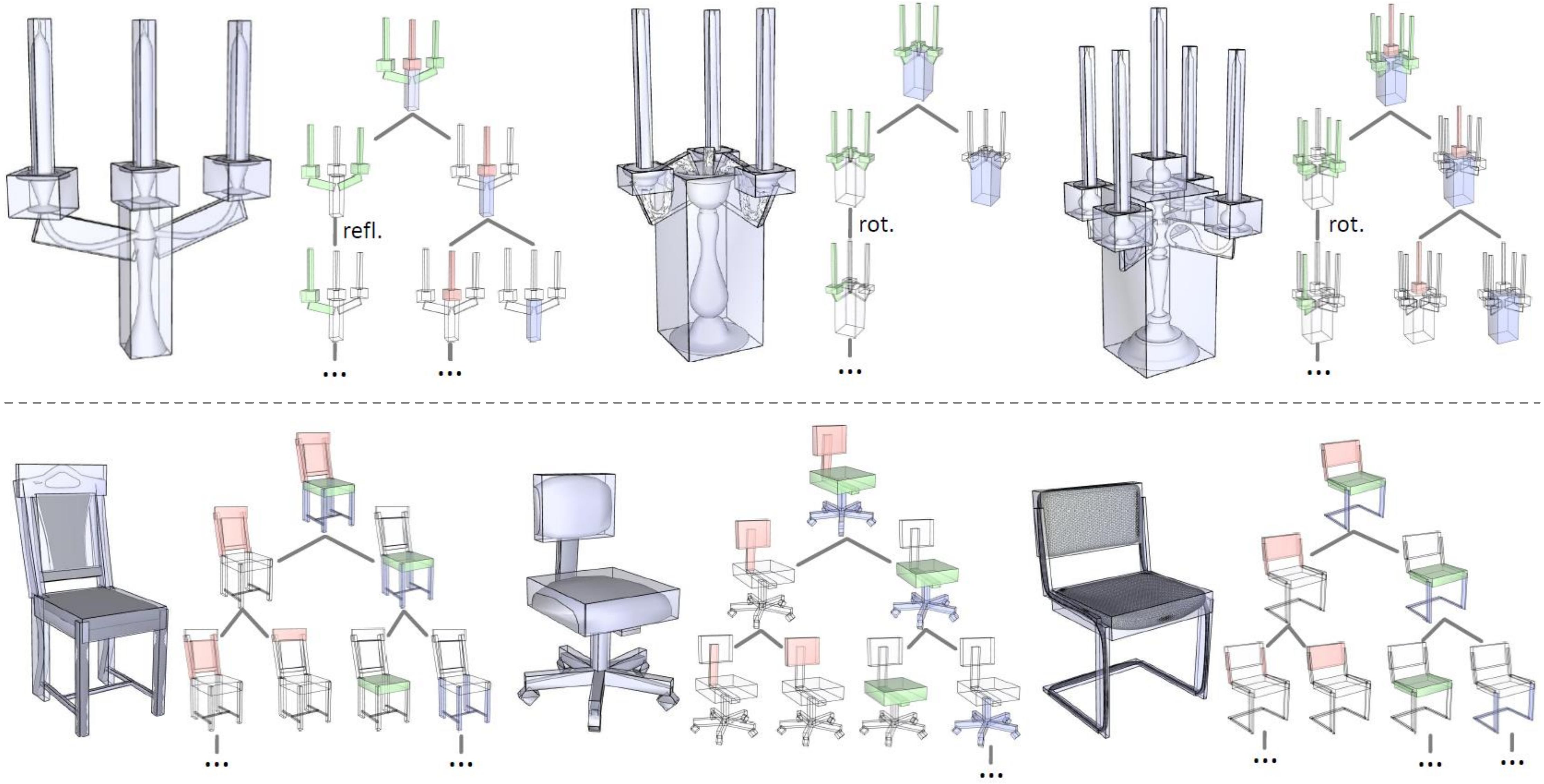




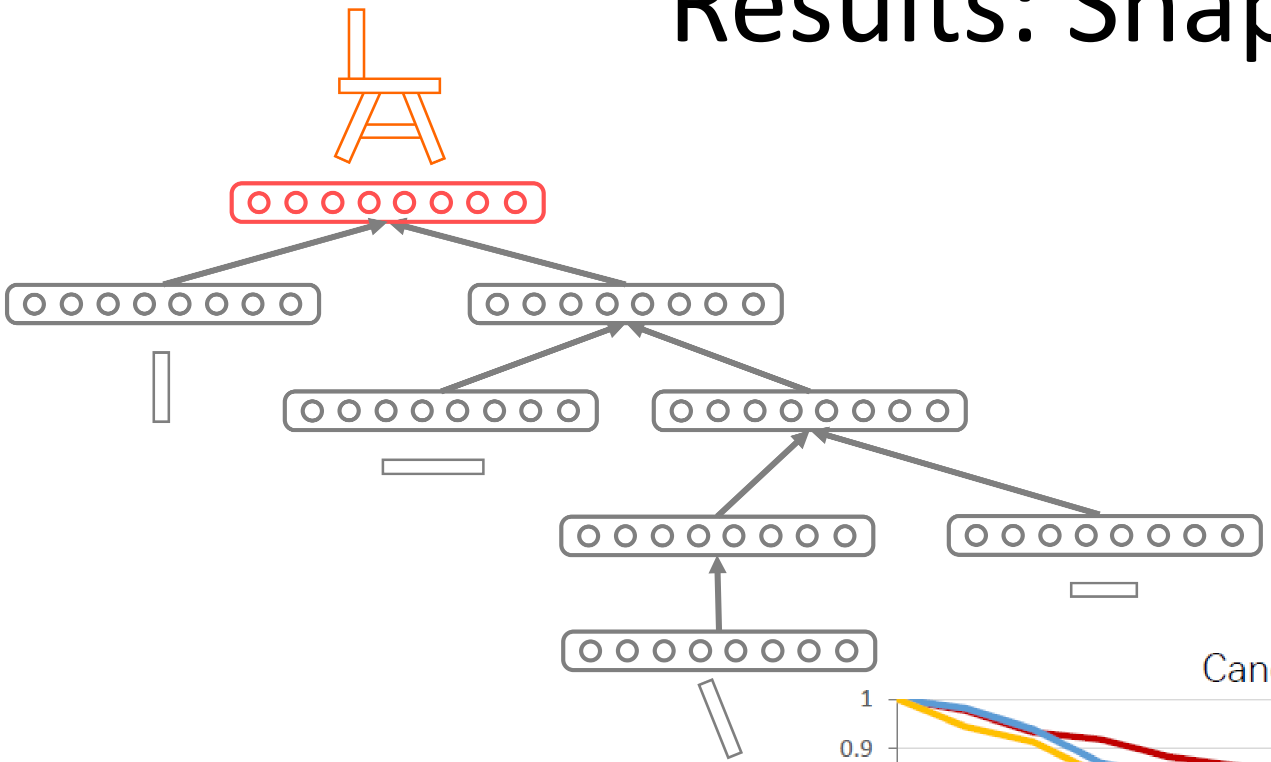
Results: Shape synthesis

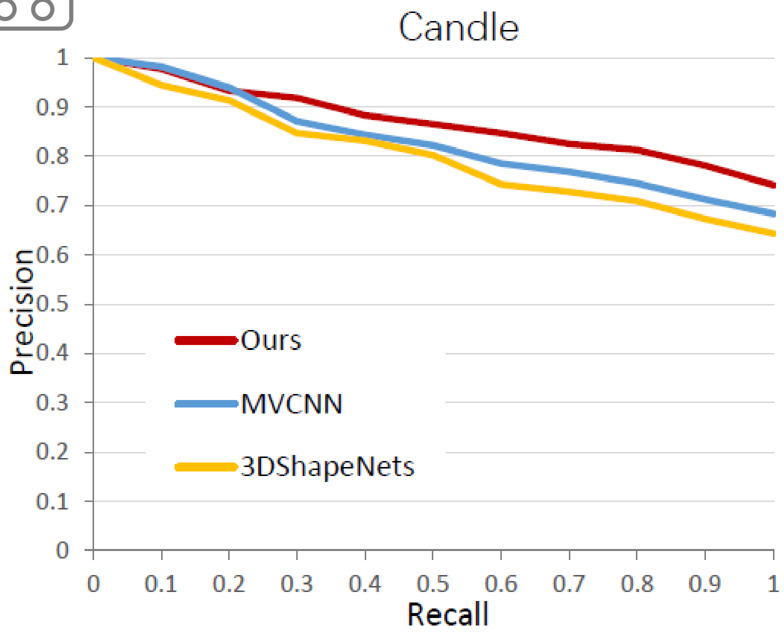


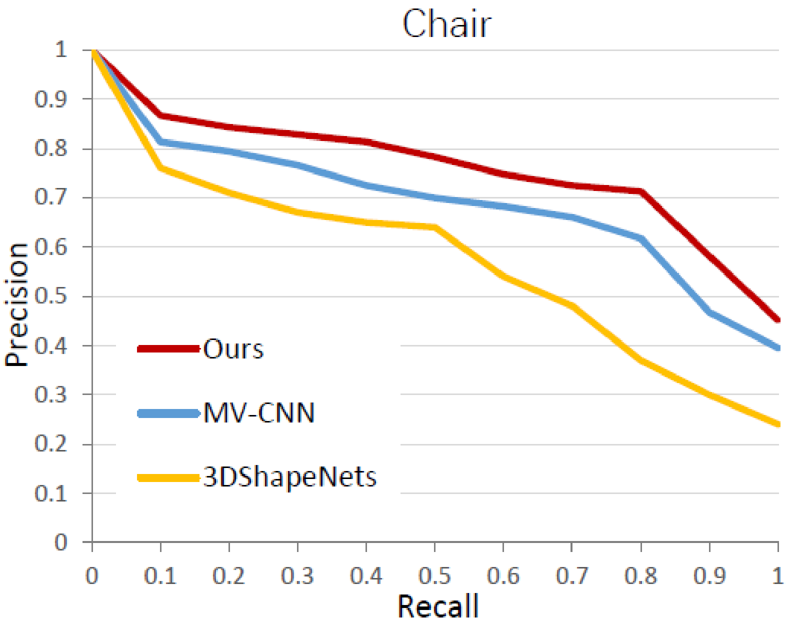
Results: Inferring consistent hierarchies



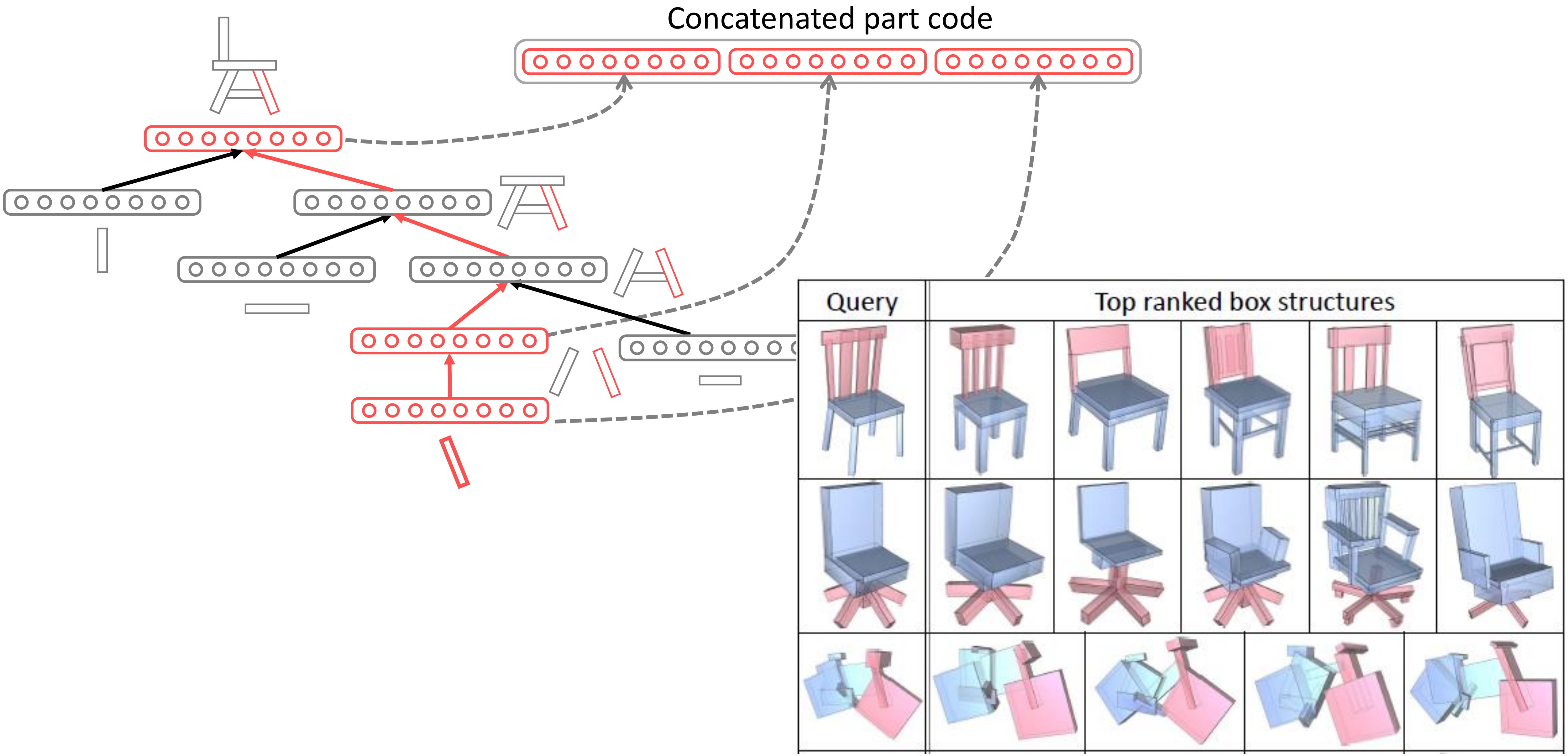
Results: Shape retrieval



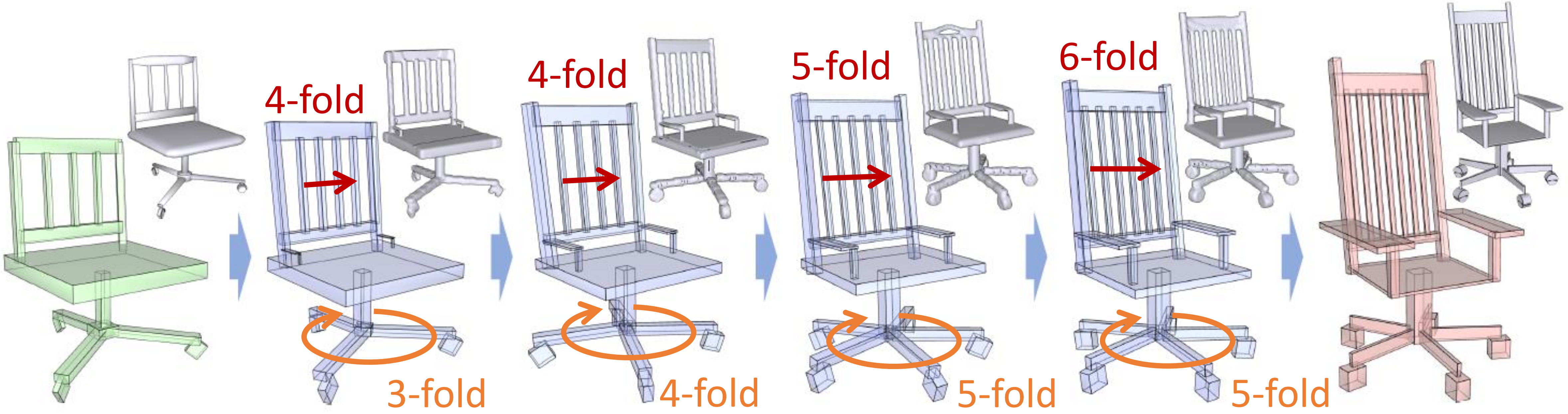




Results: Shape retrieval



Results: Shape interpolation



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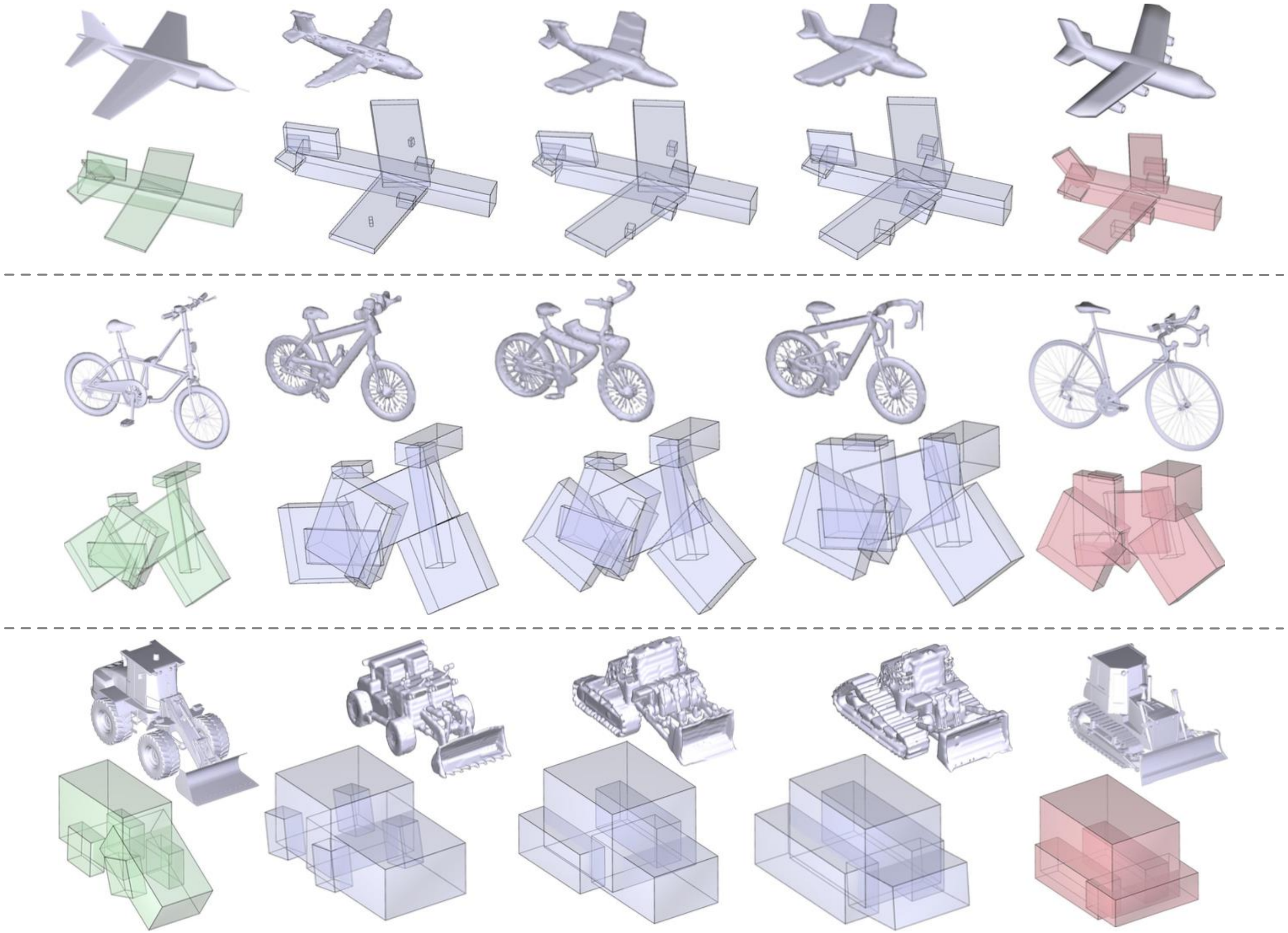
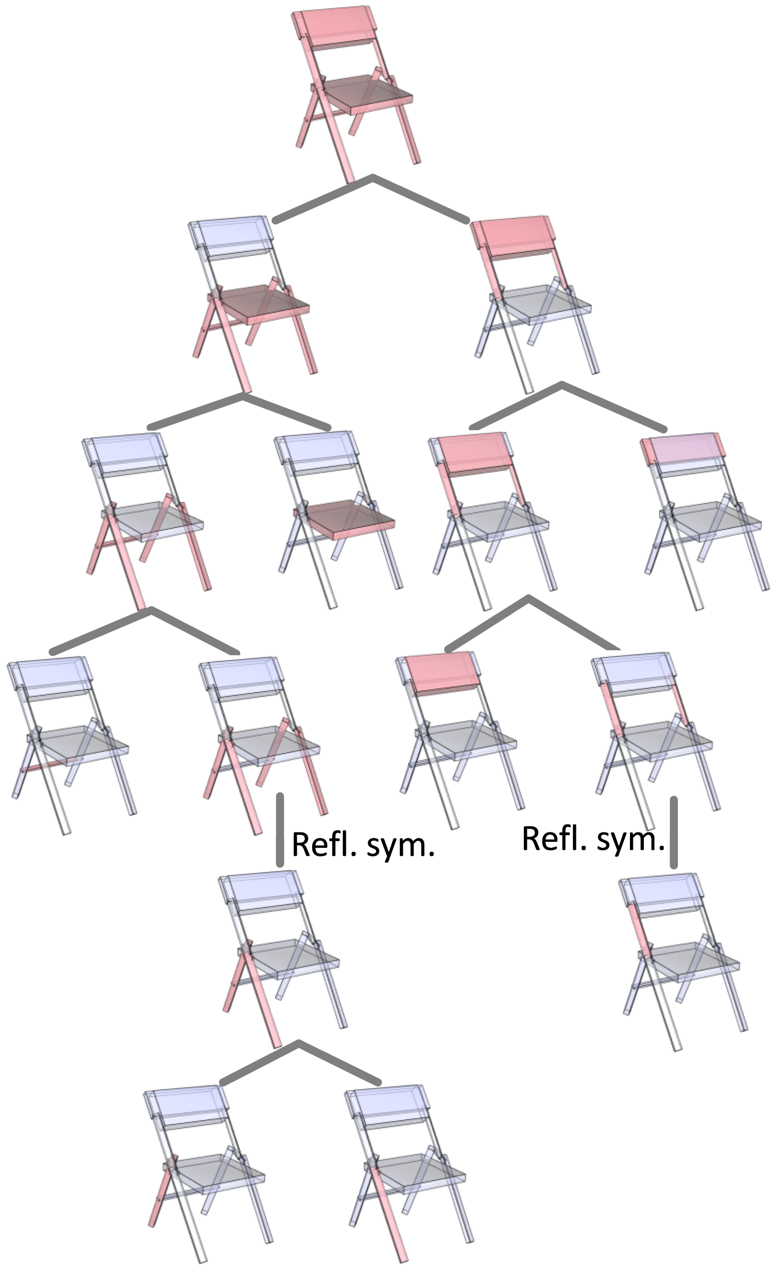


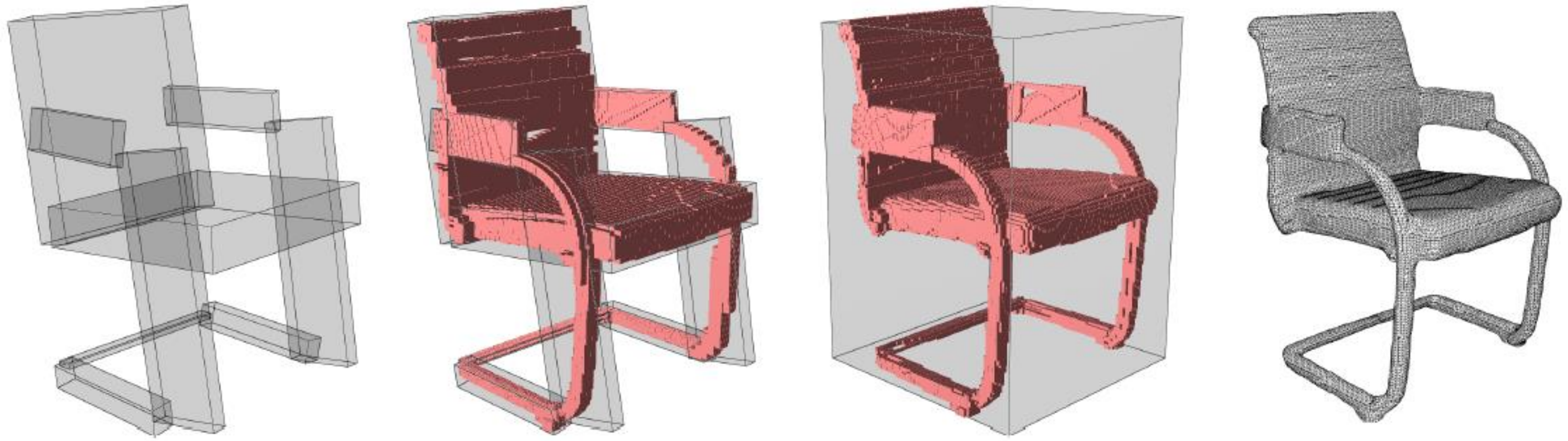
Discussion

- What does our model learn?
  - Hierarchical organization of part structures
  - A reasonable way to generate 3D structure
    - Part by part
    - Bottom-up
    - Hierarchical organization
  - This is the usual way how a human modeler creates a 3D model
    - Hierarchical scene graph



Discussion

- A general guideline for 3D shape generation
- Coarse-to-fine:
  - First generate coarse structure
  - Then generate fine details
  - May employ different representations and models



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  - Jun Li is a visiting PhD student of University of Bonn, supported by the CSC

Thank you!

Code & data available at

www.kevinkaixu.net