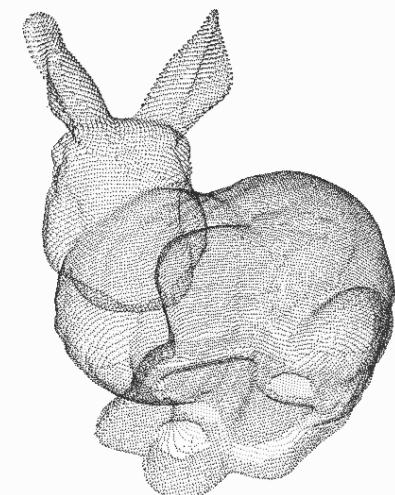
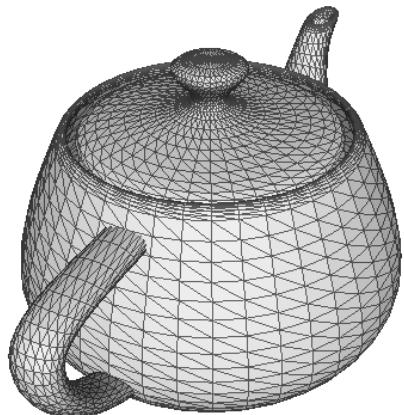


Part-based 3D Analysis

Guest Lecture: Kaichun Mo

3D Shape Understanding Tasks

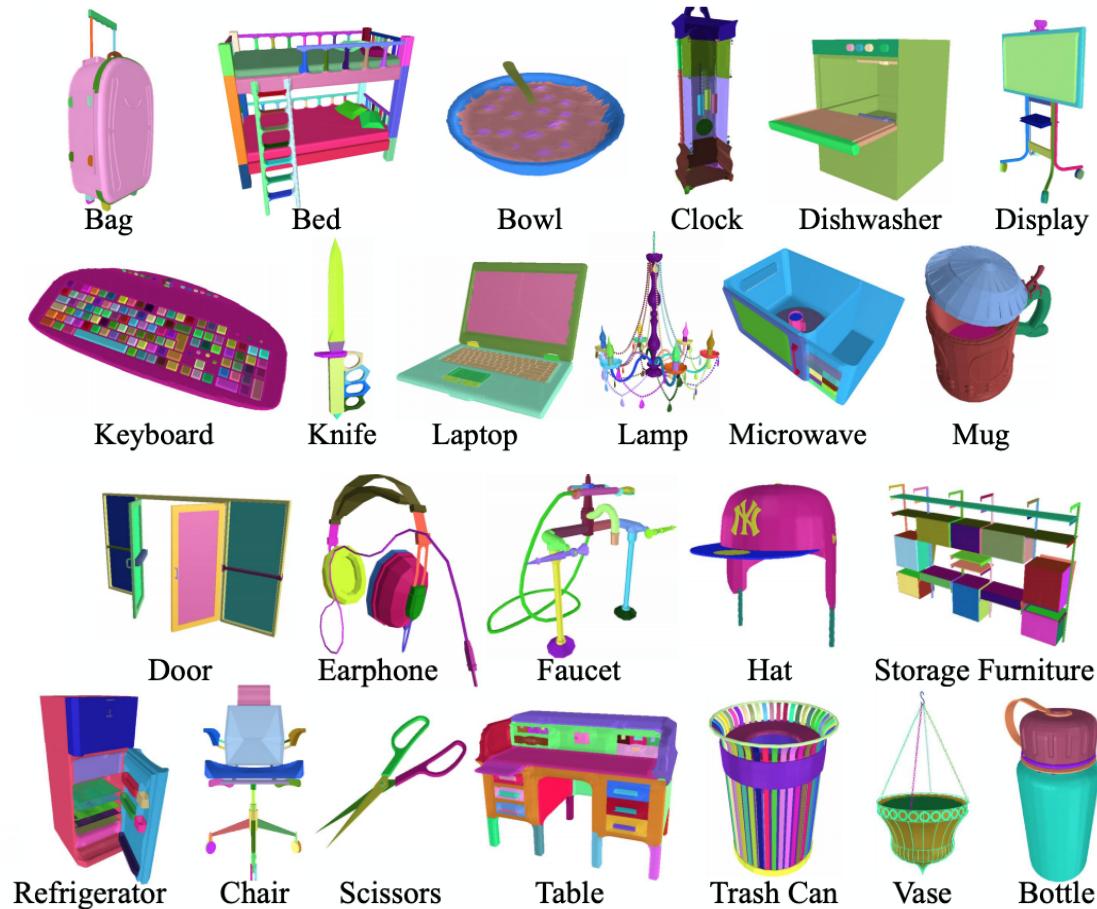


Shape Classification

Shape Detection and Segmentation

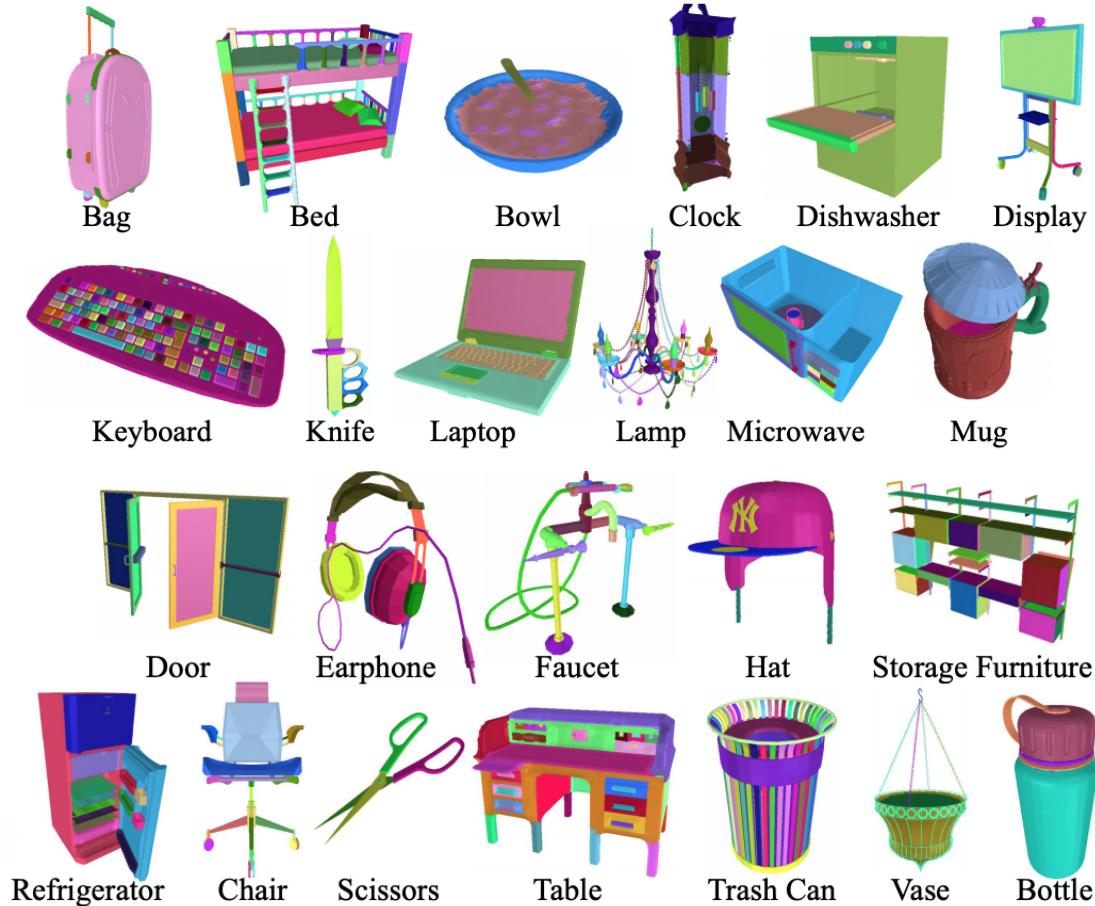
Shape Reconstruction

3D Shape Parts



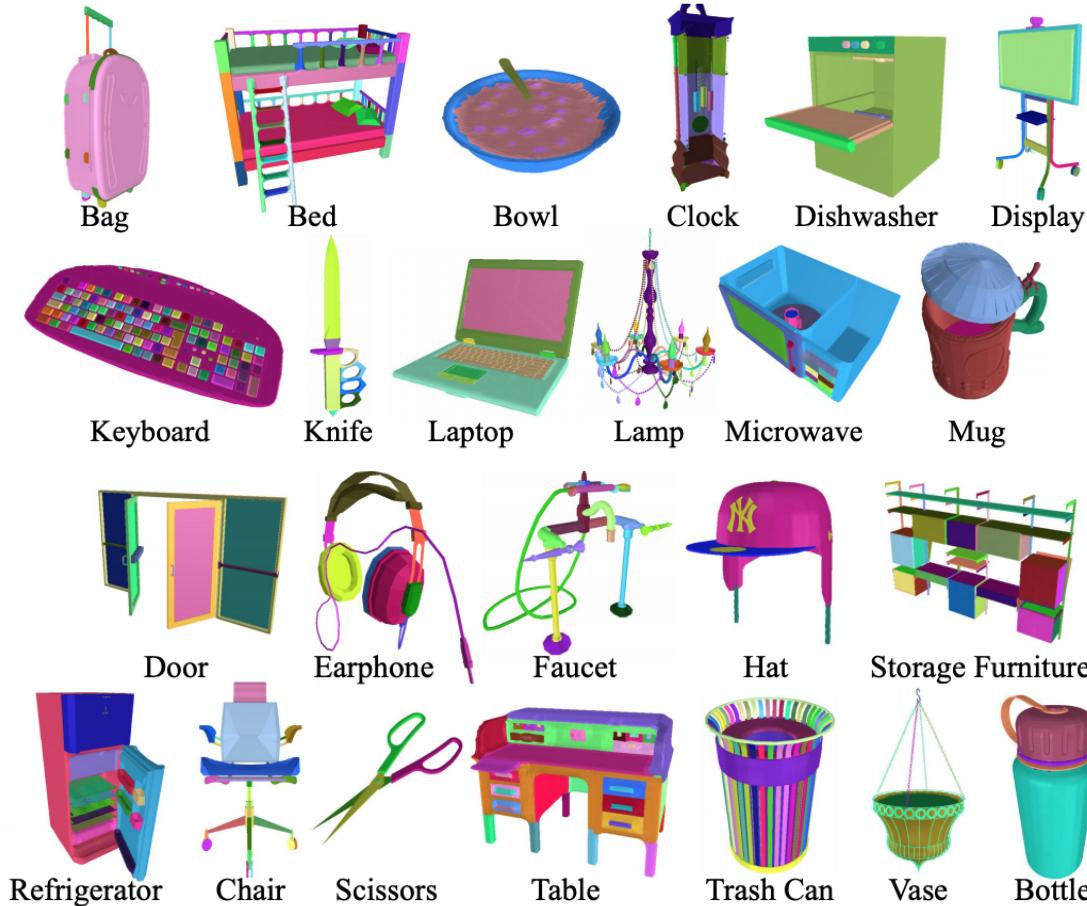
Mo et al., “**PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding**”, *CVPR 2019*

3D Shape Parts



Primitive Parts Composition

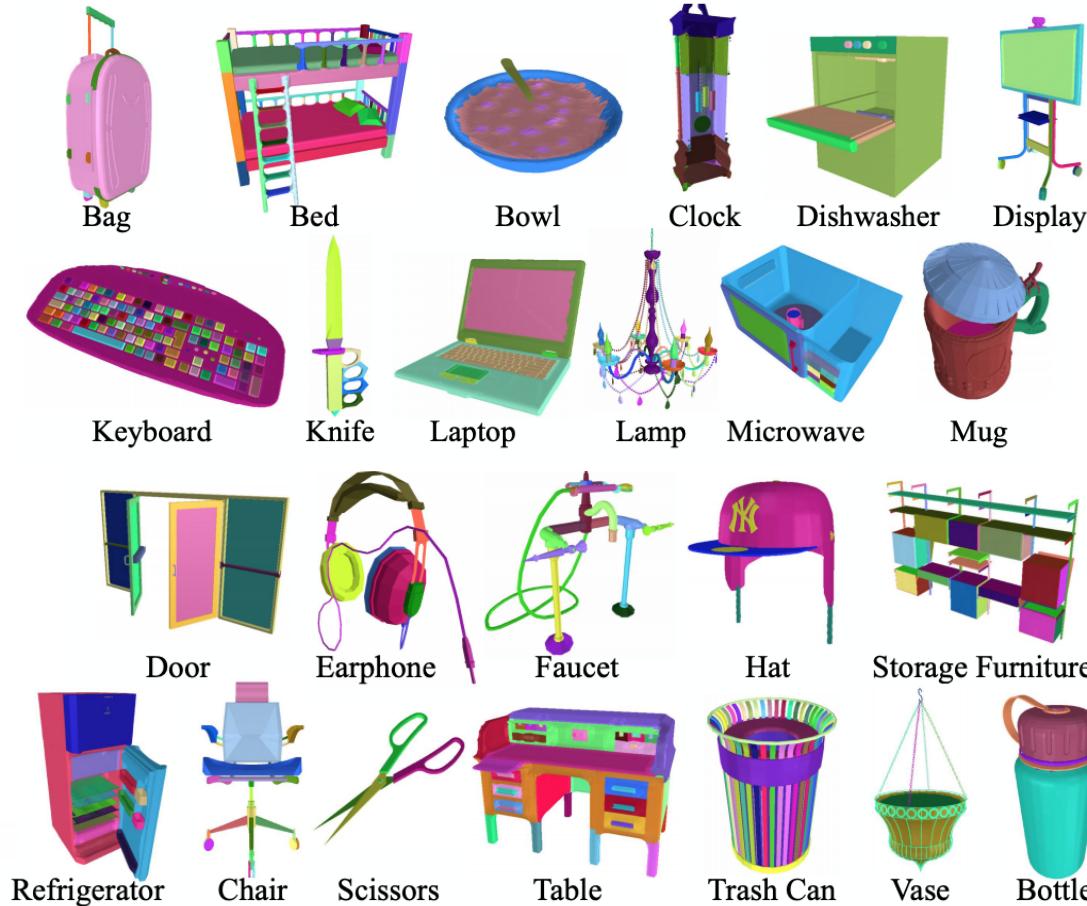
3D Shape Parts



**Primitive Parts
Composition**

**Semantics
Functionality**

3D Shape Parts



**Primitive Parts
Composition**

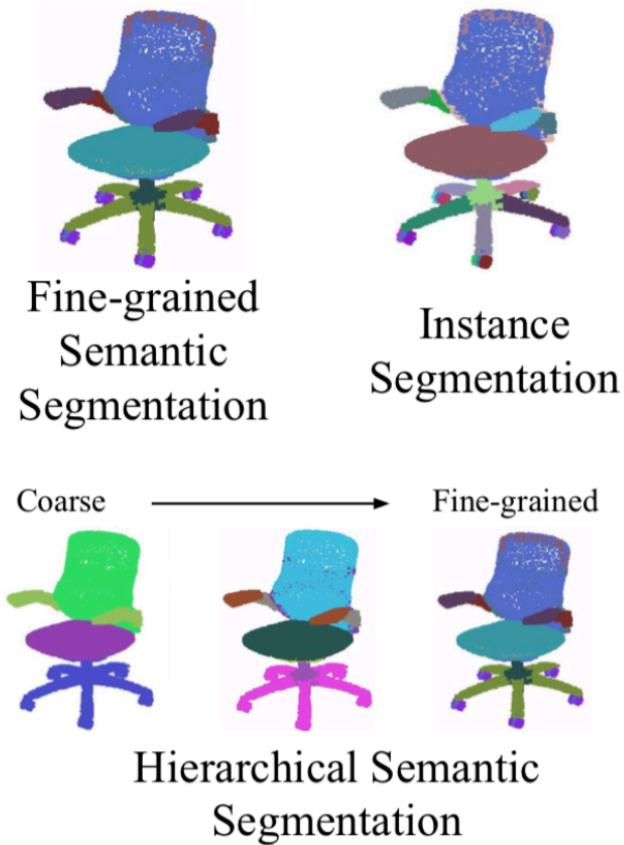
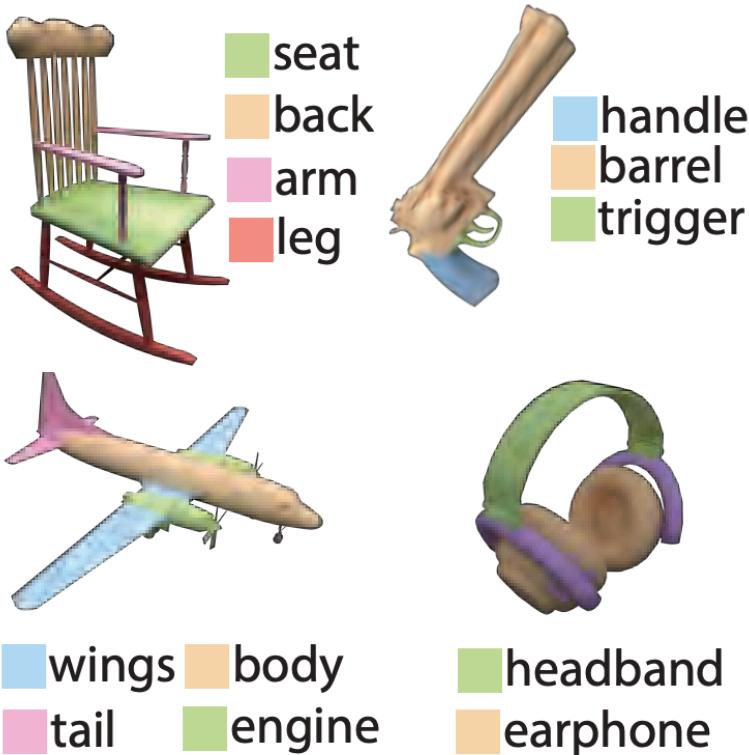
**Semantics
Functionality**

**Mobility
Interaction**

3D Shape Part Understanding Tasks

- 3D Shape Part Segmentation
- Part-based 3D Shape Generation
- Part-based 3D Shape Reconstruction
- 3D Part Relationships & Shape Structure Learning
- Understanding Part Semantics, Functionality, Mobility
- Parts as Interaction Handles

3D Shape Part Segmentation

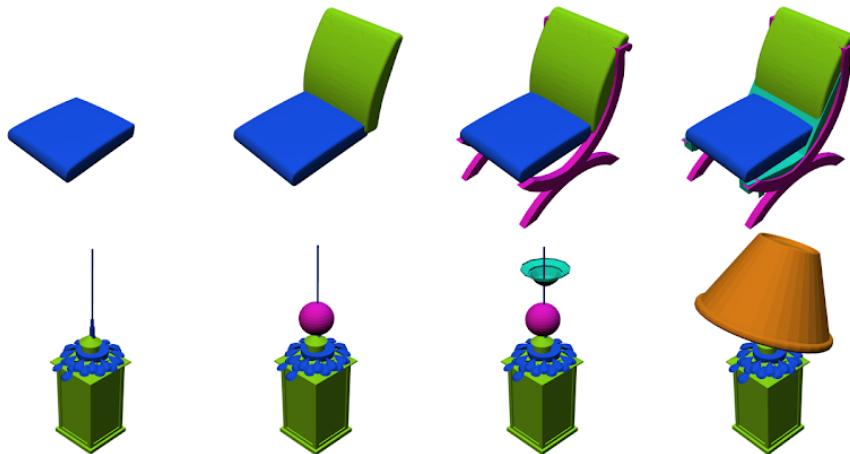


Yi et al., "A Scalable Active Framework for Region Annotation in 3D Shape Collections", *Siggraph Asia 2016*

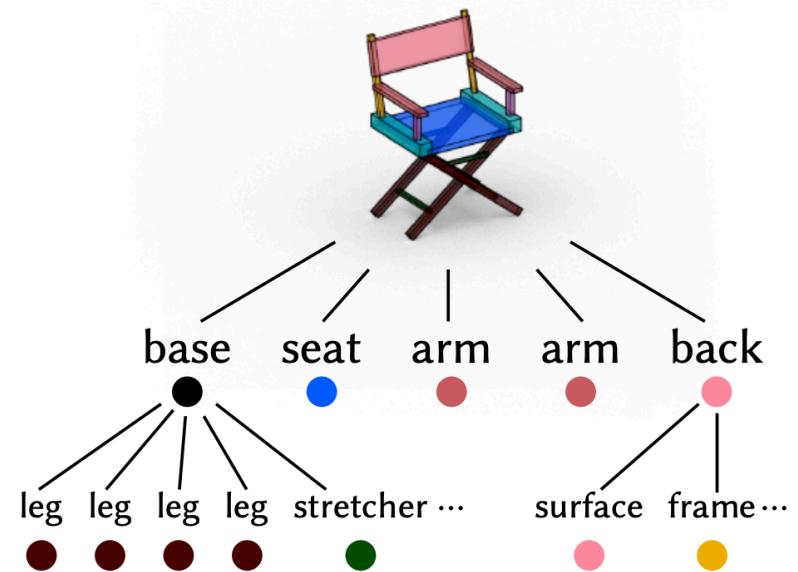
Mo et al., "PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding", *CVPR 2019*

3D Shape Generation

Part Assembly



Hierarchical Generation



Sung et al., “ComplementMe: Weakly-Supervised Component Suggestions for 3D Modeling”, *Siggraph Asia 2017*

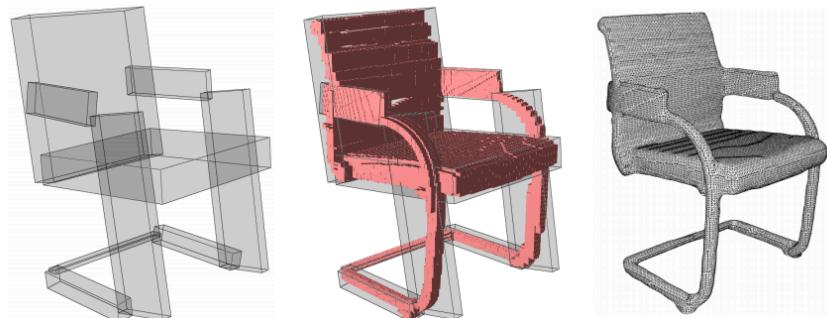
Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

3D Shape Reconstruction

Image/Scan → Part Boxes



Part Boxes → Geometry



Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

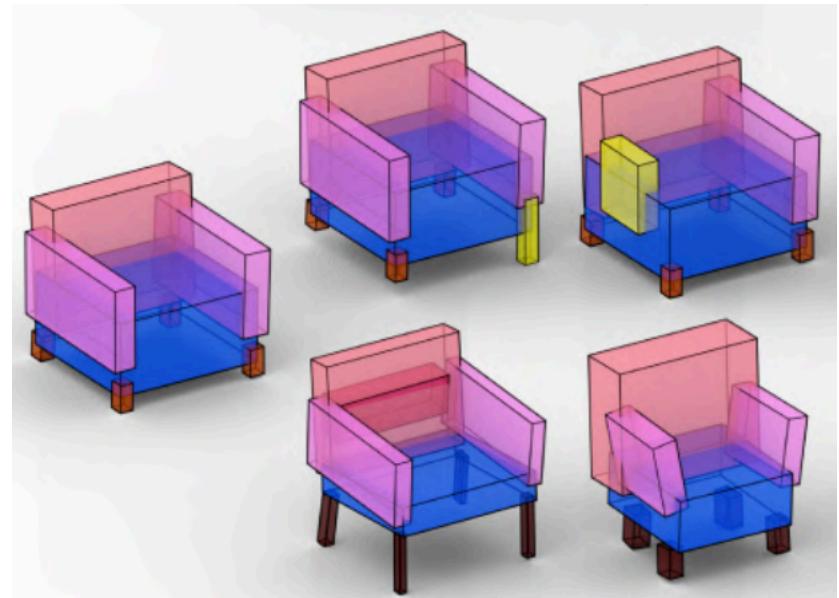
Li et al., “**Generative Recursive Autoencoders for Shape Structures**”, *Siggraph 2017*

3D Part Symmetry & Relationships

Shape Completion



Shape Editing



Mitra et al., “Partial and Approximate Symmetry Detection for 3D Geometry”, *Siggraph 2006*

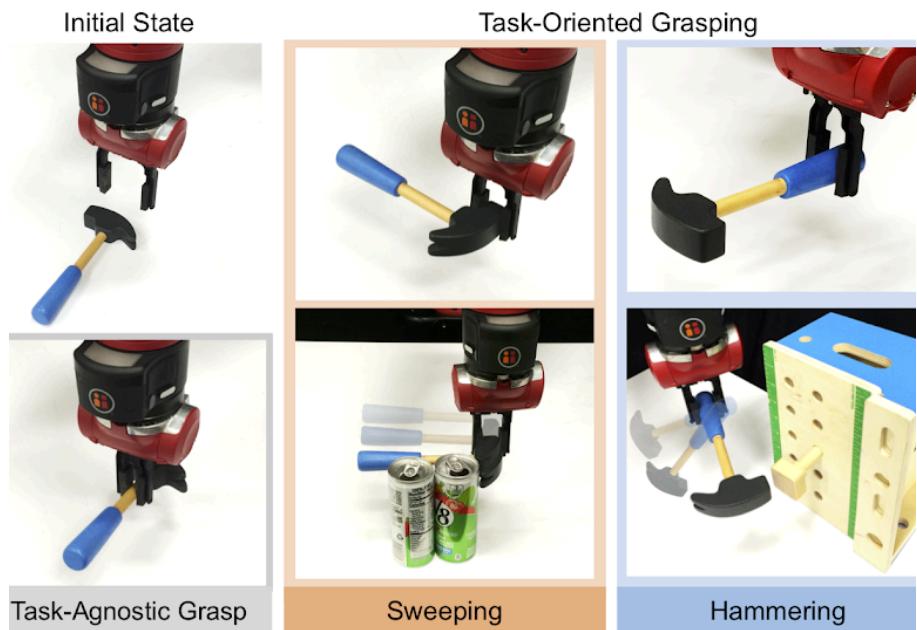
Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

3D Shape Part Functionality

Part Affordance



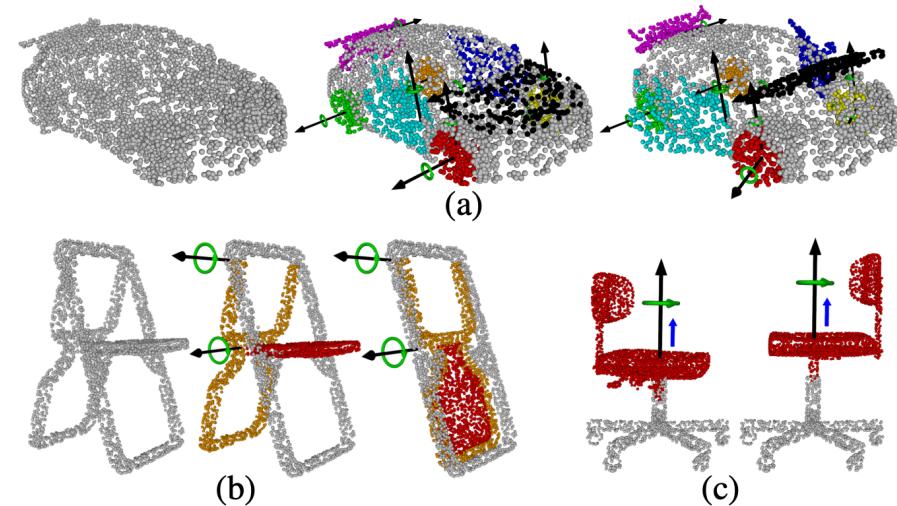
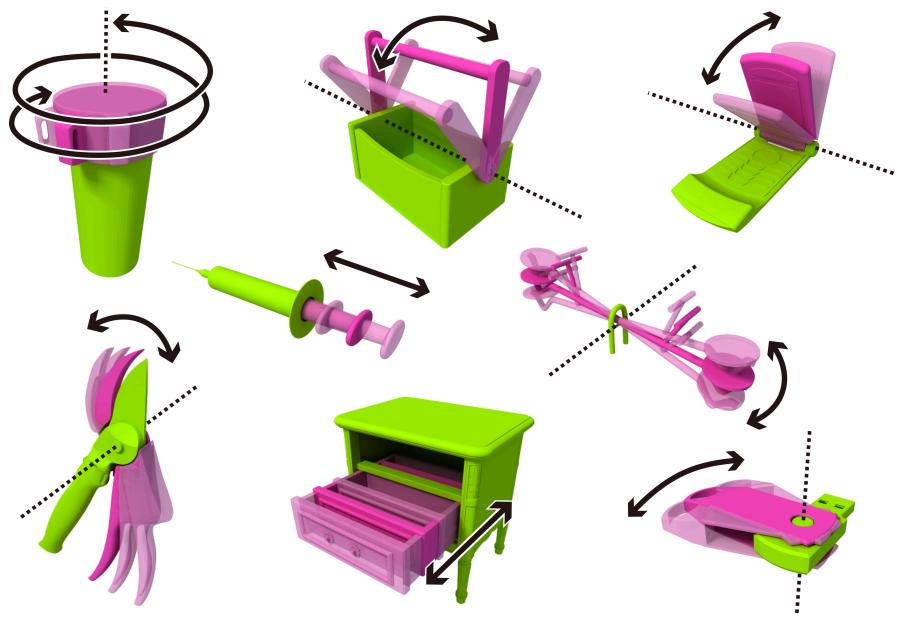
Parts for Grasping



Hu et al., “Functionality Representations and Applications for Shape Analysis”, *Computer Graphics Forum 2018*

Fang et al., “Learning Task-Oriented Grasping for Tool Manipulation from Simulated Self-Supervision”, *RSS 2018*

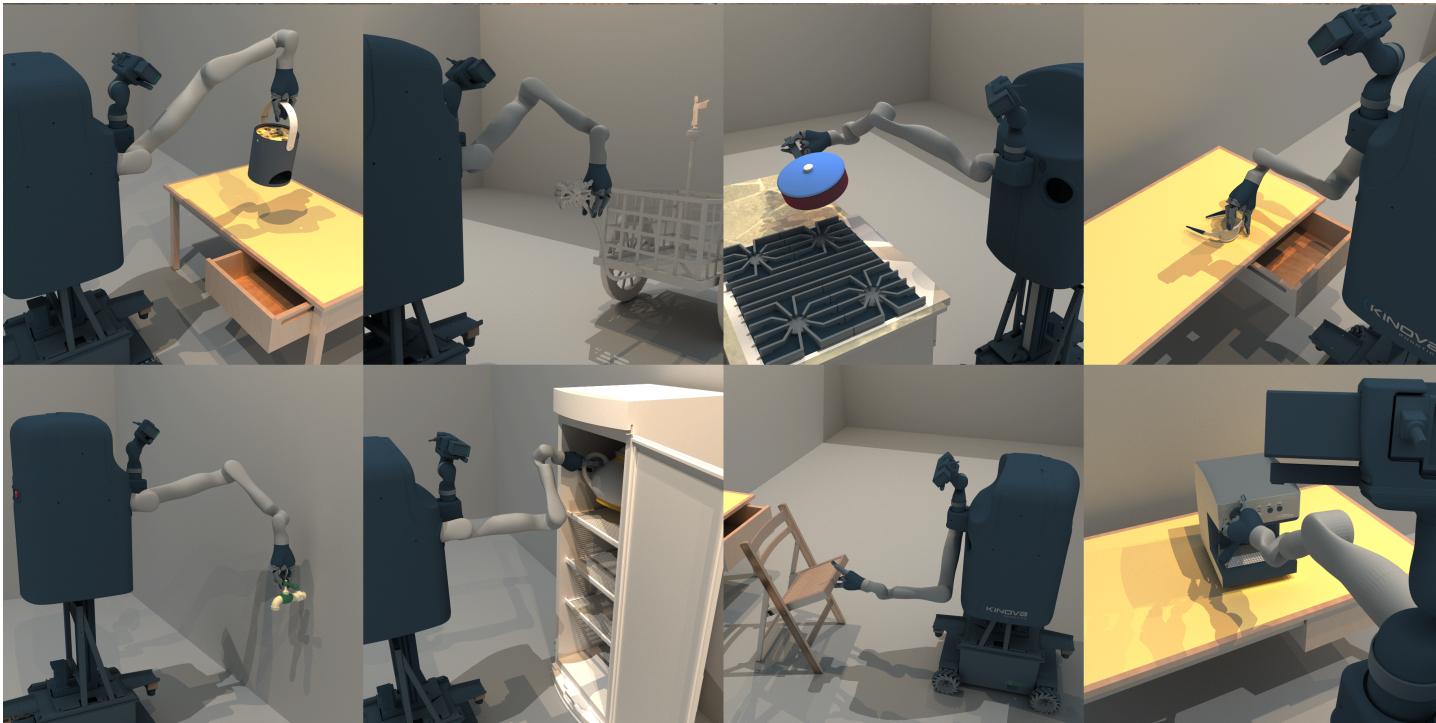
Part Mobility



Hu et al., "Learning to Predict Part Mobility from a Single Static Snapshot", *Siggraph Asia 2017*

Wang et al., "Shape2Motion: Joint Analysis of Motion Parts and Attributes from 3D Shapes", *CVPR 2019*

Parts as Interaction Handles



Xiang et al., “SAPIEN: A SimulAted Part-based Interactive ENvironment”, CVPR 2020

Parts as Interaction Handles



Xiang et al., “SAPIEN: A SimulAted Part-based Interactive ENvironment”, CVPR 2020

Agenda

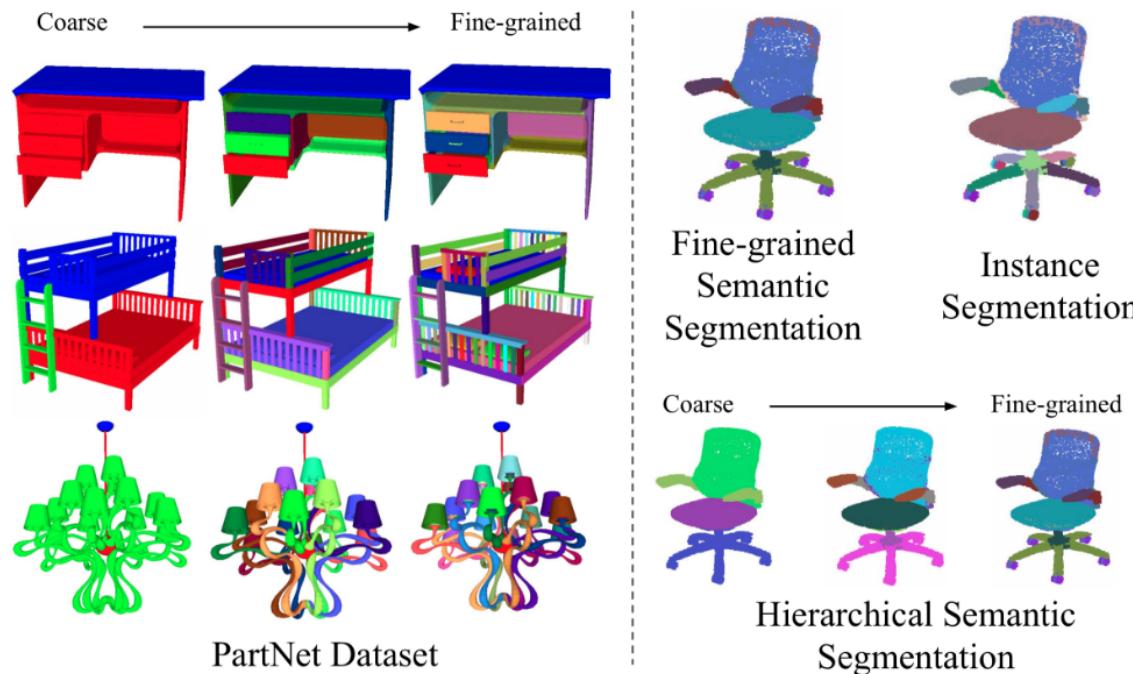
- Part Annotation and Datasets
- 3D Shape Part Segmentation
- Part-based 3D Shape Generation

Part Annotation and Datasets

Part Semantics Taxonomy and Ambiguity

Part Annotation and Datasets

Large-scale Human-annotated Datasets are essential for advancing the development of 3D architecture research



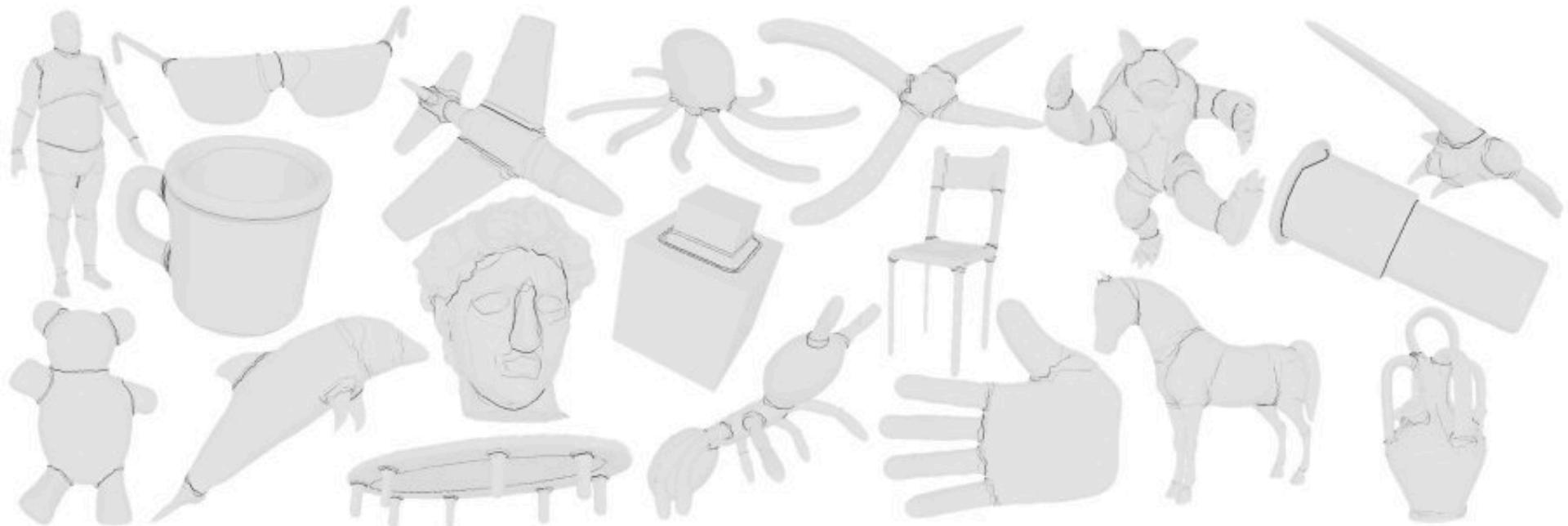
Training Data for Networks Evaluation Benchmarks

Mo et al., “PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding”, CVPR 2019

Princeton Segmentation Benchmark

Early Dataset dated back to 2009

(19 Categories, 380 Shapes, avg 11 parts per shape)



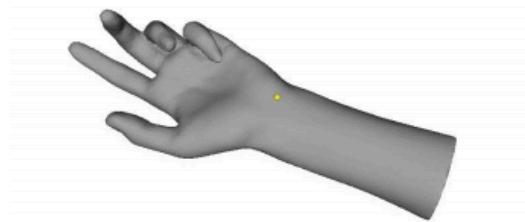
Human Annotated (8 people)

Probabilistic “Ground-truth”

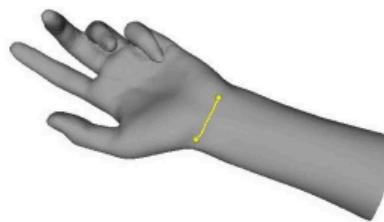
<https://segeval.cs.princeton.edu/>

Princeton Segmentation Benchmark

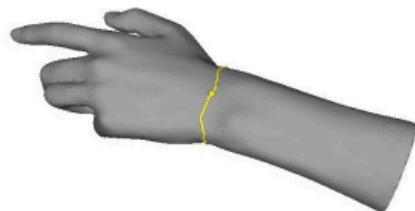
Human annotated in 3D Interactive GUI



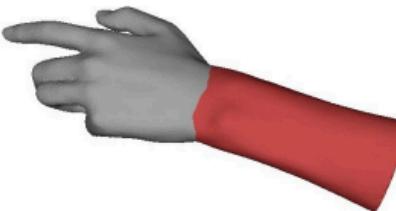
(a) After one click



(b) After two clicks



(c) After three clicks



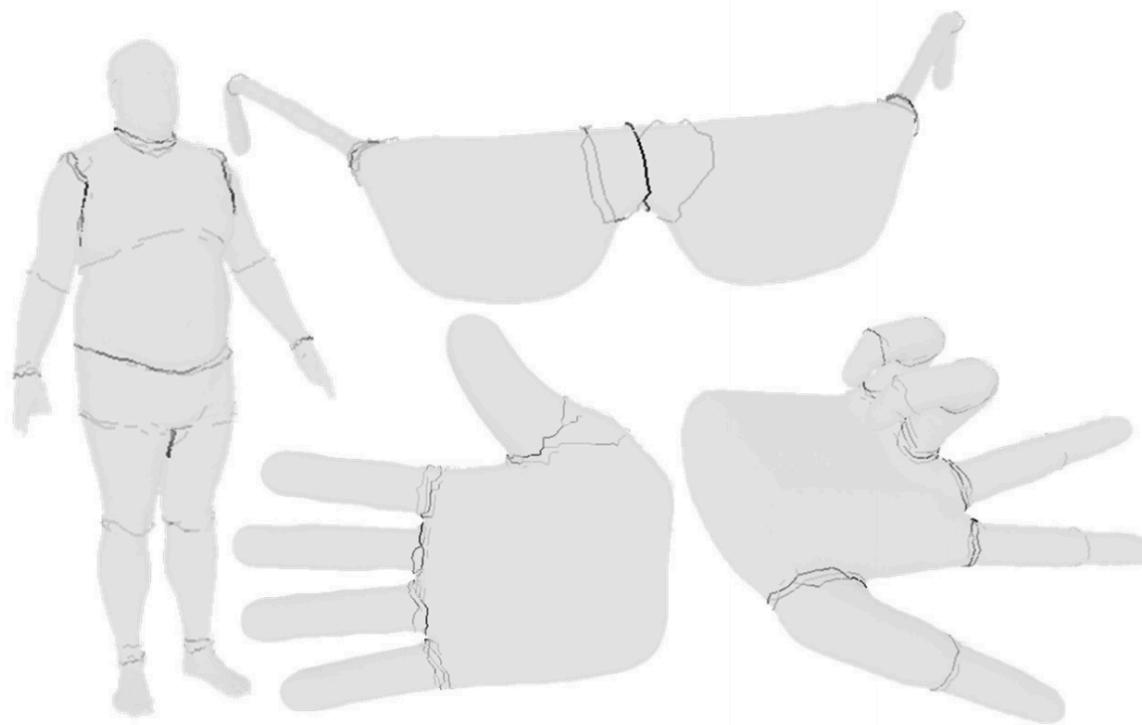
(d) After making the cut

3D Annotation is Time-consuming

<https://segeval.cs.princeton.edu/>

Princeton Segmentation Benchmark

Parts are ambiguous, subjective and hierarchical:
Different annotators provide different segmentation



Probabilistic “Ground-truth”

<https://segeval.cs.princeton.edu/>

ShapeNet Dataset (>3M Shapes)

3D CAD Modeling: SketchUp, Yobi3D, Fusion360

chair
a seat for one person, with a support for the back; 'he put his coat over the back of the chair and sat down'
[ImageNet](#) [MetaData](#)

Choose a taxonomy:

ShapeNetCore

- airplane,aeroplane,plane(12,4501)
- aquarium,fish tank,marine museum(0,4)
- ashcan,trash can,garbage can,wastebin,ash bin(0,1)
- bag,traveling bag,travelling bag,grip,suitcase(1,1)
- basket,handbasket(2,140)
- bathtub,bathing tub,bath,tub(0,932)
- bed(13,353)
- bench(5,1953)
- birdhouse(0,79)
- boat(12,1635)
- bookshelf(0,495)
- bottle(6,550)
- bowl(1,234)
- bus,autobus,coach,charabanc,double-decker,j
- cabinet(9,1644)
- camera,photographic camera(4,134)
- can,tin,tin can(2,108)
- cap(4,81)
- car,auto,automobile,machine,motorcar(18,244)
- cellular telephone,cellular phone,cellphone,cell(1,1)
- chair(23,7083)

Synset models

Displaying 1 to 40 of 7080

< 1 2 3 4 5 6 7 8 9 10 11 12 13 ... 177 >


club chair


cantilever chair


armchair


straight chair


straight chair


club chair


deck chair


rex chair


straight chair


club chair


club chair


swivel chair


butterfly chair


armchair


armchair


club chair


recliner


cantilever chair


swivel chair


swivel chair


armchair


folding chair


rocking chair


club chair


green chair


orange chair


brown chair


green chair


black chair


brown chair

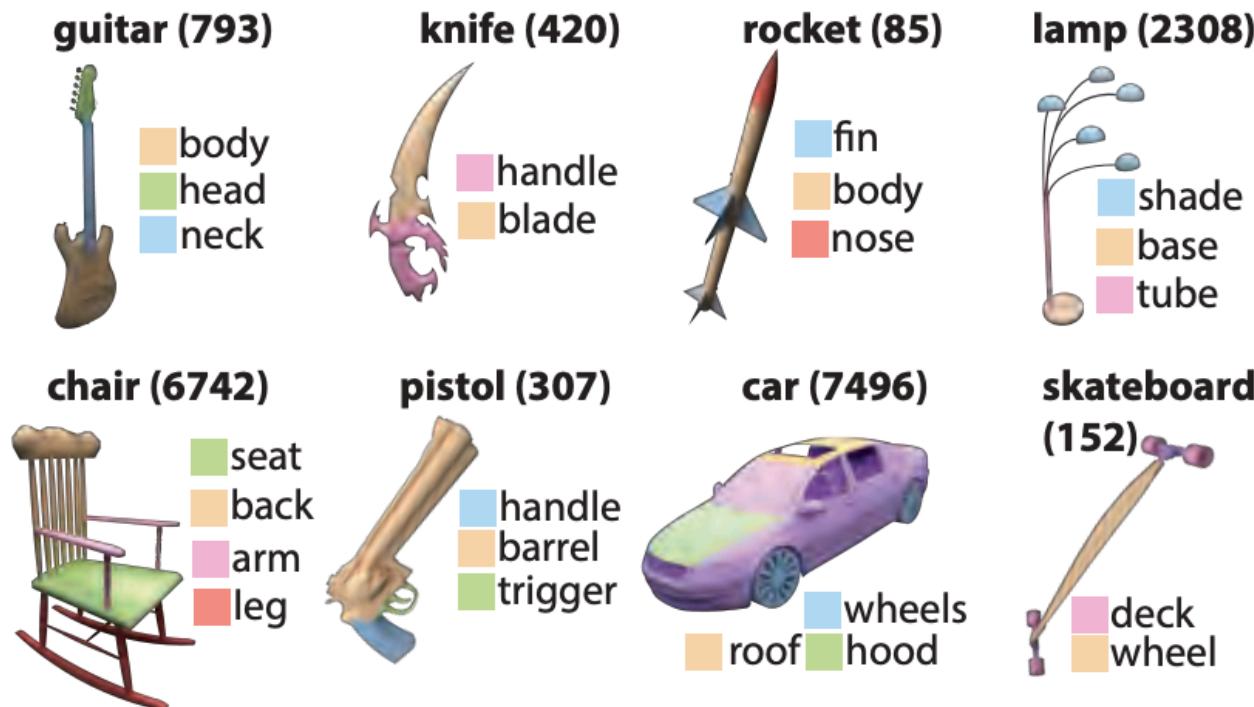

orange chair


brown chair

Chang et al., “ShapeNet: An Information-Rich 3D Model Repository”, SGP Dataset Awards

ShapeNet-Part Dataset

16 Categories, 31K Shapes, avg 3 parts per shape



Consistent Ground-truth Semantics

Yi et al., “A Scalable Active Framework for Region Annotation in 3D Shape Collections”, *Siggraph Asia 2016*

PartNet Dataset

More Fine-grained Part Annotations



- seat
- back
- arm
- leg

ShapeNet-Part



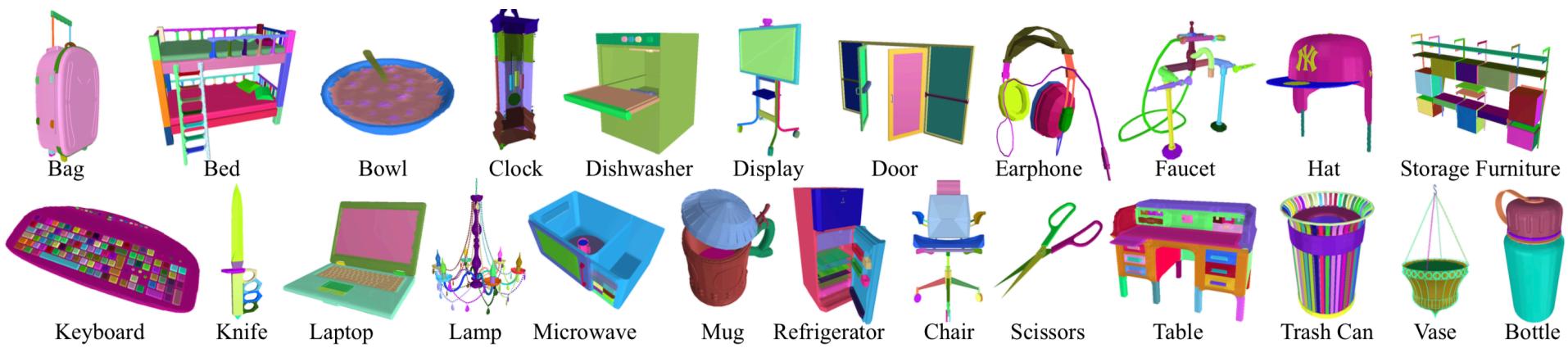
PartNet

Small Parts may be Important!

Mo et al., "PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding", CVPR 2019

PartNet Dataset

24 categories, 26,671 shapes, avg 22 parts per shape



Mo et al., “**PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding**”, *CVPR 2019*

PartNet Dataset

Difficulty 1: How to define consistent part semantics?

PartNet Dataset

Difficulty 1: How to define consistent part semantics?

Difficulty 2: How to organize parts at different granularity?

PartNet Dataset

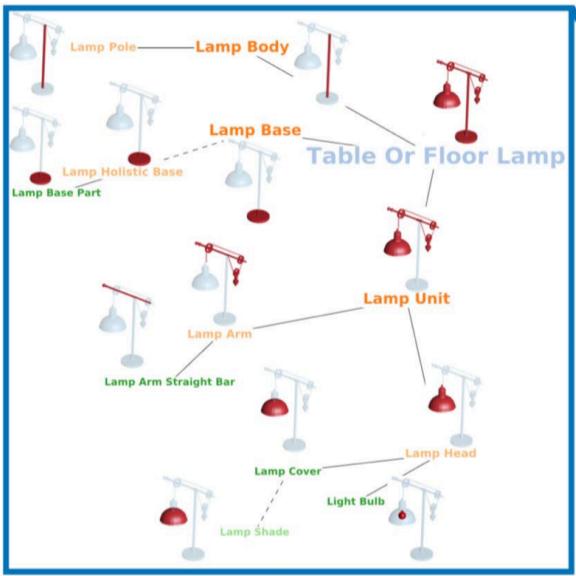
Difficulty 1: How to define consistent part semantics?

Difficulty 2: How to organize parts at different granularity?

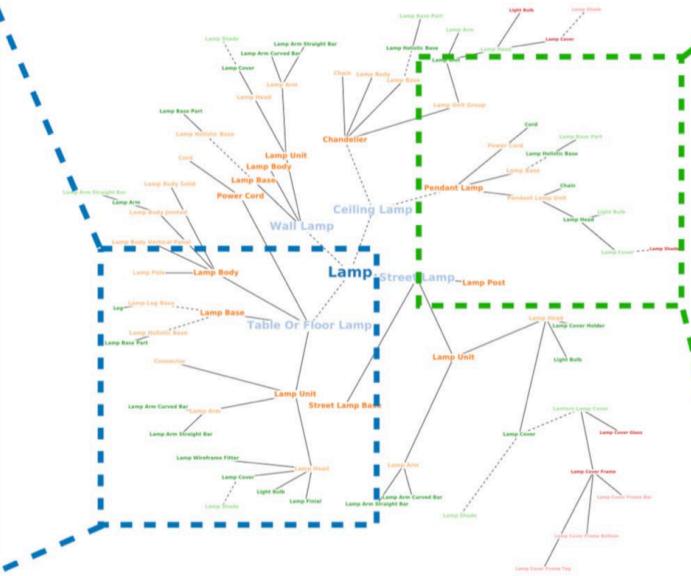
Difficulty 3: How to represent the rich part relationships and shape structures?

PartNet Dataset

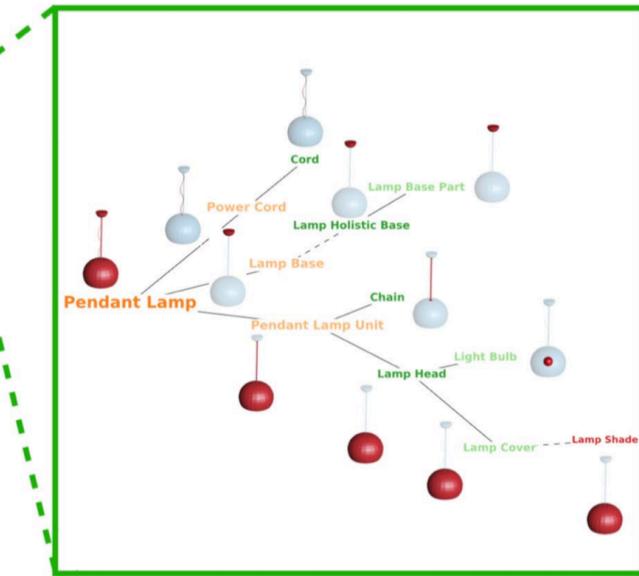
Per-category Canonical And-or-graph Template



One Table Lamp Example



Part Template



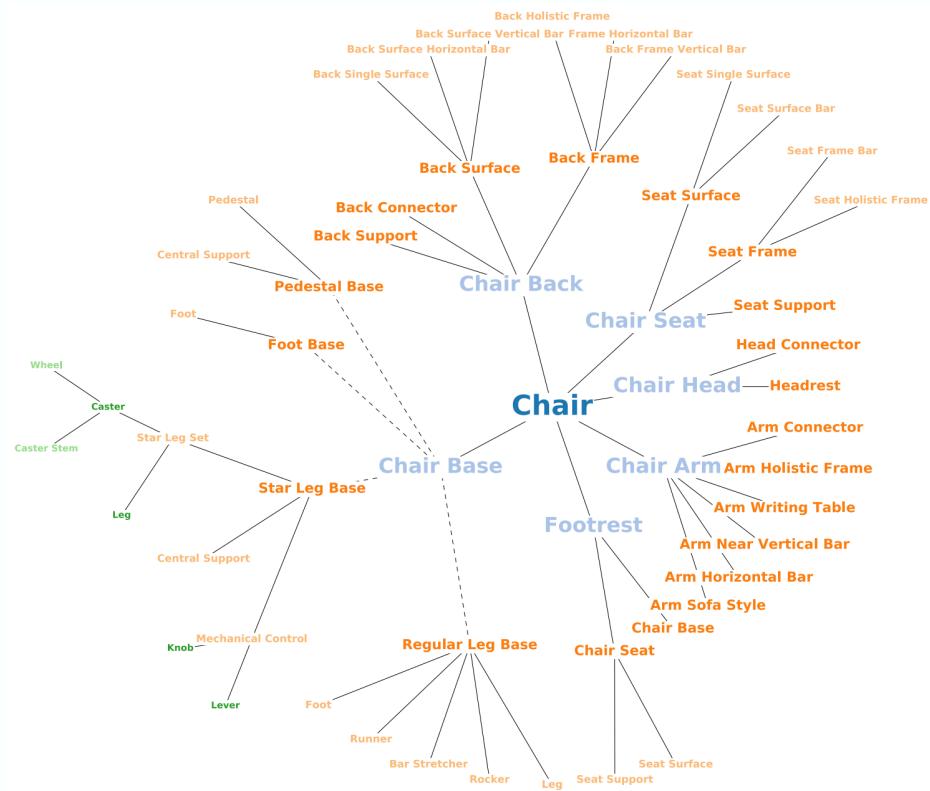
One Floor Lamp Example

Consistent Semantics Across Shapes

Mo et al., "PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding", CVPR 2019

PartNet Dataset

Per-category Canonical And-or-graph Template



Expert-defined Semantics

And: Sub-components

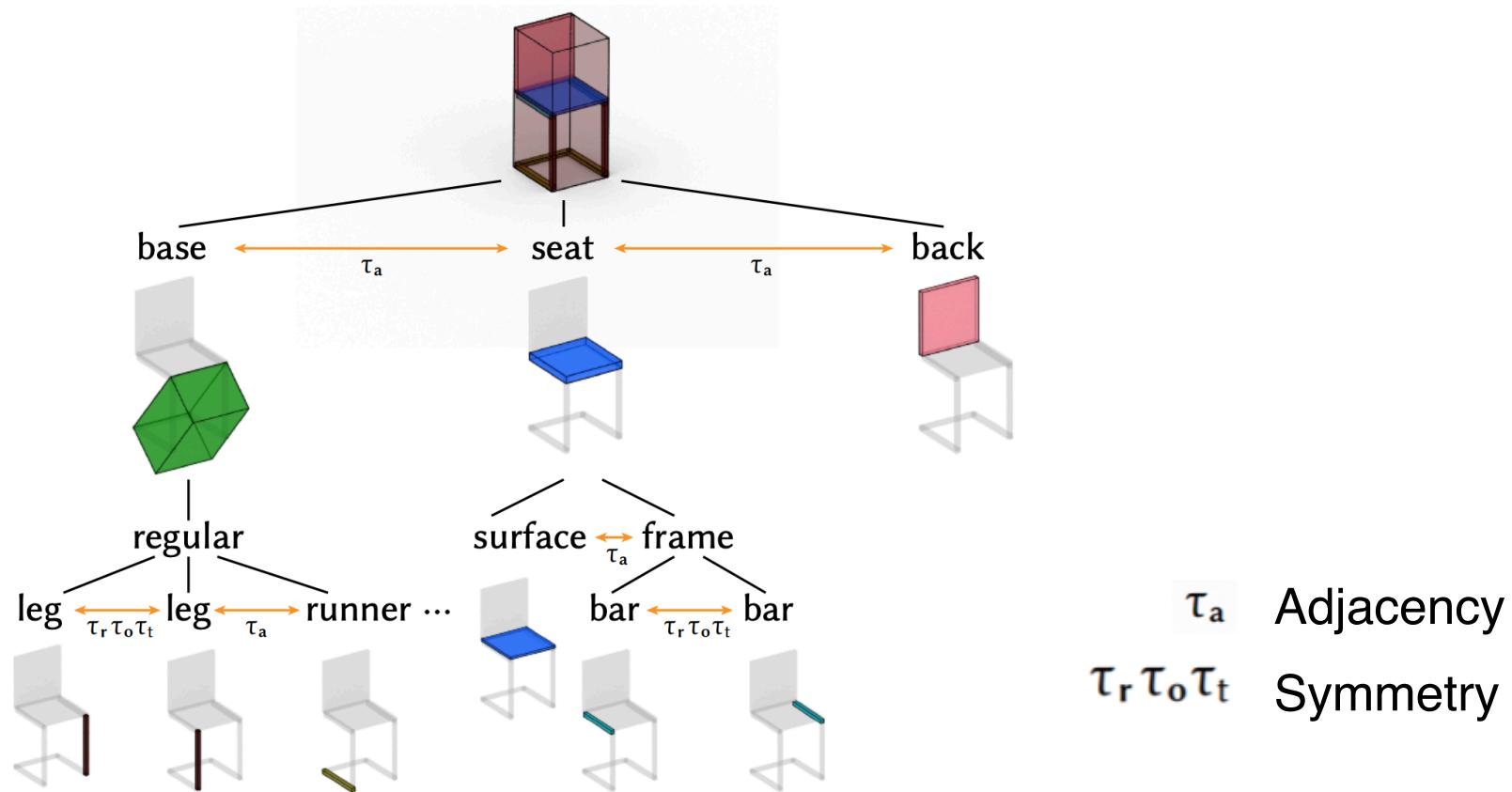
Or: Sub-types

Consistent Semantics Across Shapes

Mo et al., "PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding", CVPR 2019

PartNet Dataset

Describe Rich Part Relationships



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, Siggraph Asia 2019

Summary

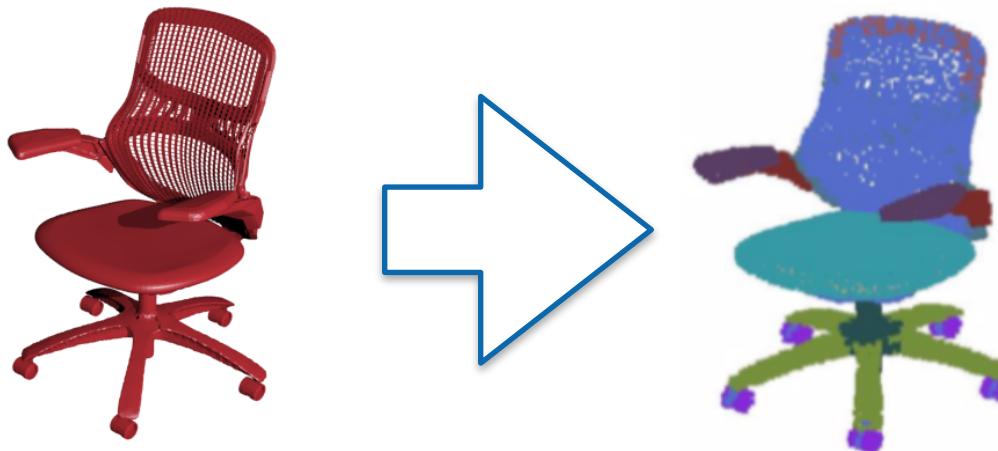
- Part definitions are ambiguous and subjective
- Parts have multiple granularity levels
- Shape has rich part relationships and structures
- Part Annotations are expensive and time-consuming

3D Shape Part Segmentation

Semantic-level, Instance-level, Hierarchical

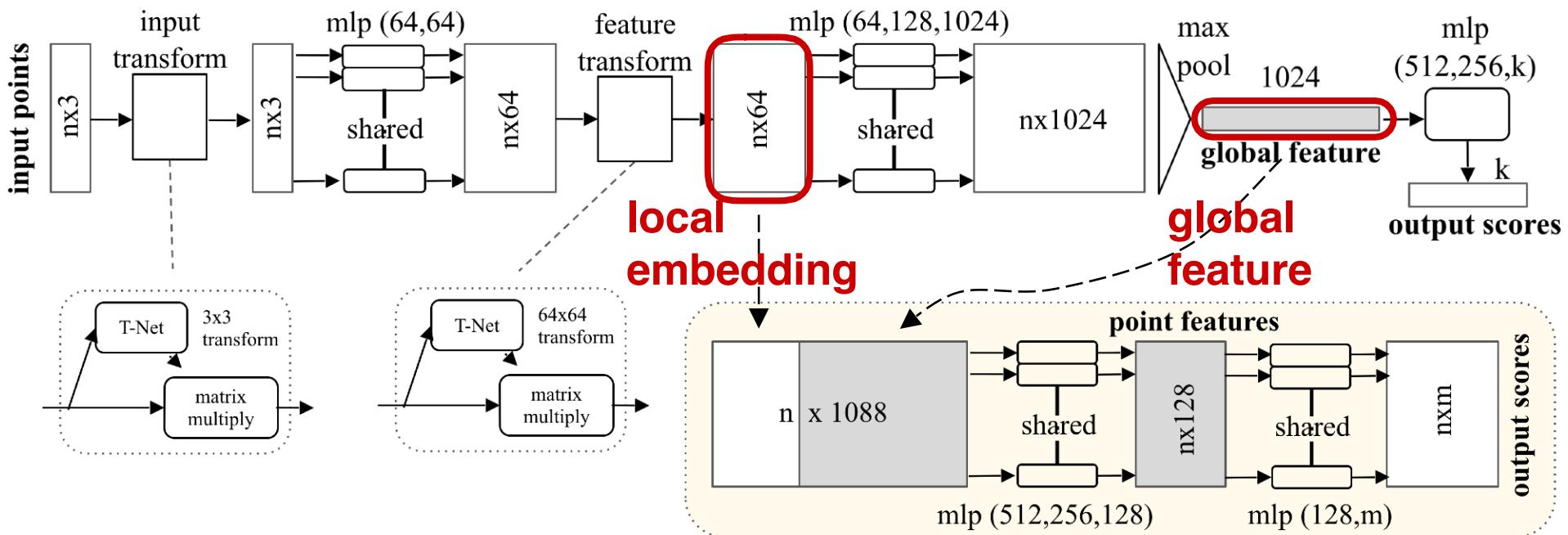
Part Semantic Segmentation

We do NOT need to separate five leg part instances
(we know there are m kinds of part semantics)



Do you recall anything from previous lectures?

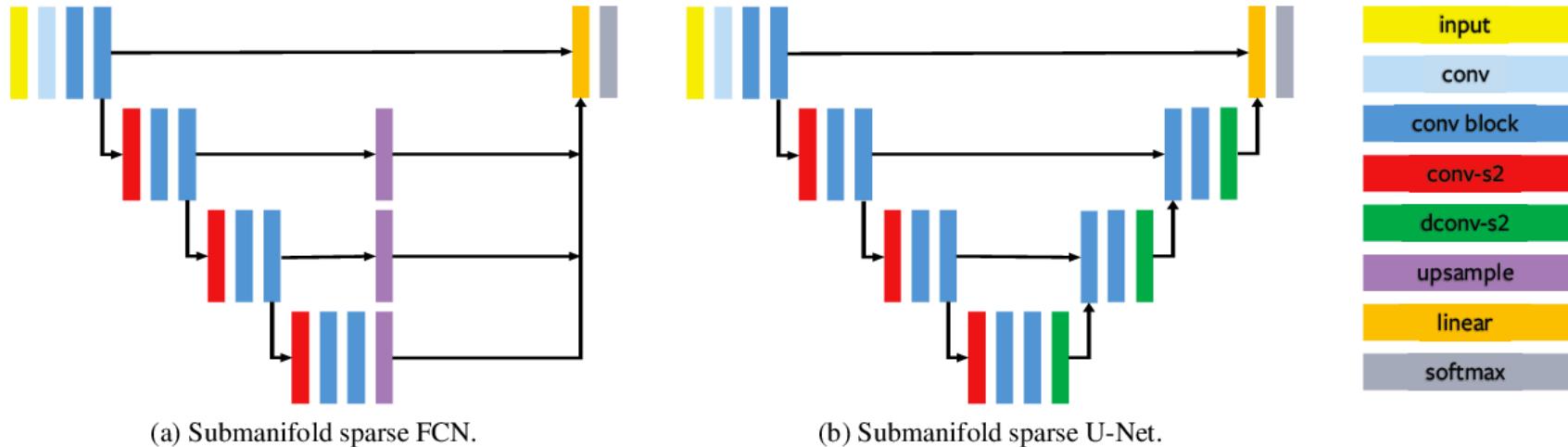
PointNet Segmentation Network



Qi et al., "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation", CVPR 2017

Review previous lectures

ConvNet Segmentation Network



Graham et al., “Submanifold Sparse Convolutional Networks”, arxiv

Review previous lectures

Other Segmentation Networks

Mesh-based

Kalogerakis et al., “Learning 3D Mesh Segmentation and Labeling”, *Siggraph 2010*

Hanocka et al., “MeshCNN: A Network with an Edge”, *Siggraph 2019*

Image-based

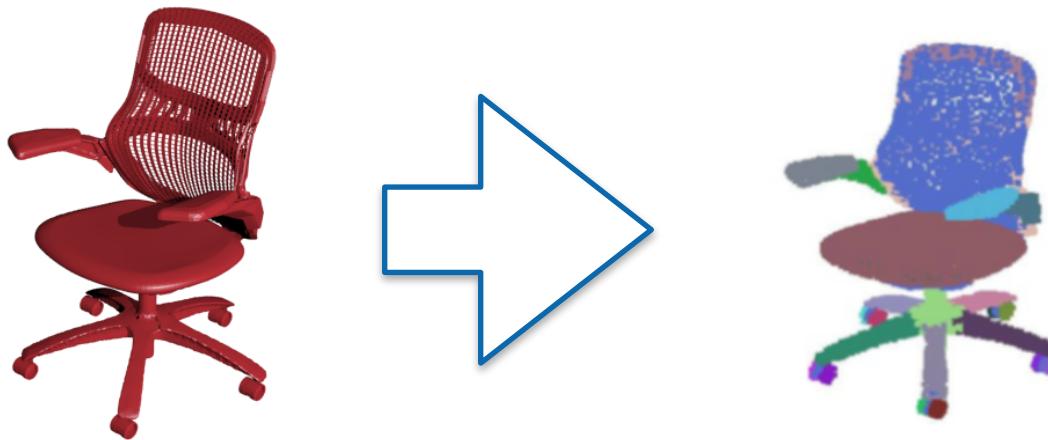
Kalogerakis et al., “3D Shape Segmentation with Projective Convolutional Networks”, *CVPR 2017*

Huang et al., “Learning Local Shape Descriptors from Part Correspondences with Multiview Convolutional Networks”, *Siggraph 2018*

Read by yourself

Part Instance Segmentation

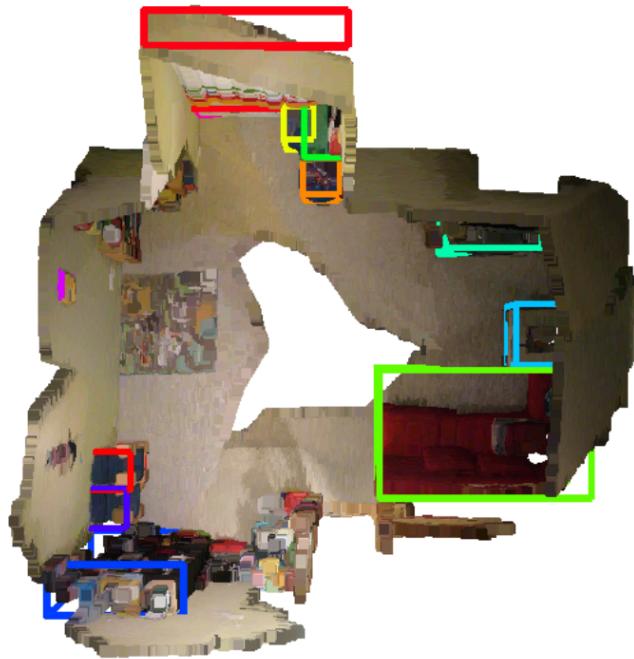
We have to separate five leg part instances
(we do NOT know part count in total)



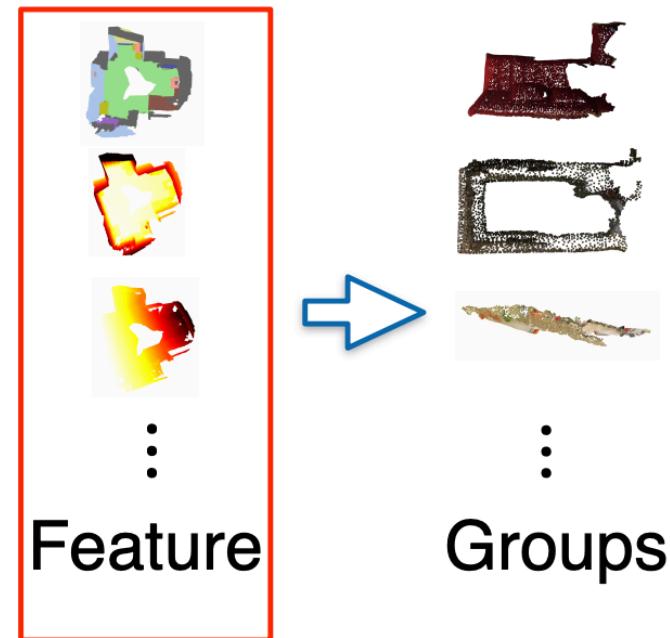
What does this remind you of?

3D Instance Segmentation

Top-down Approaches



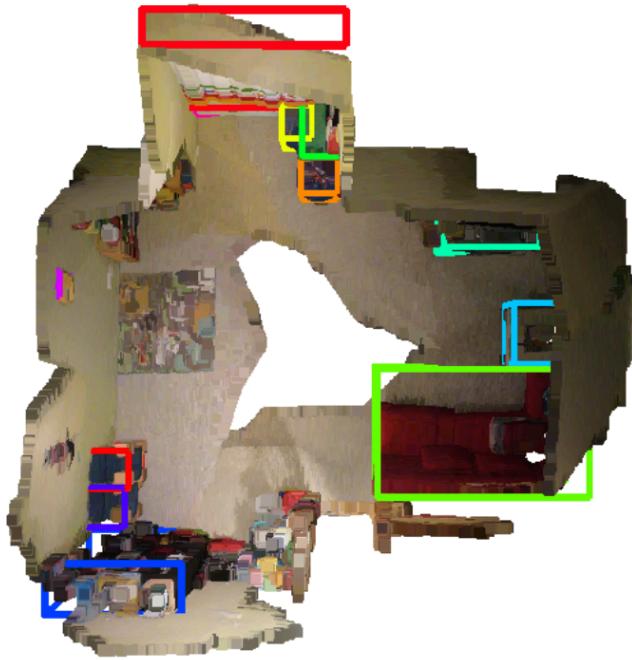
Bottom-up Approaches



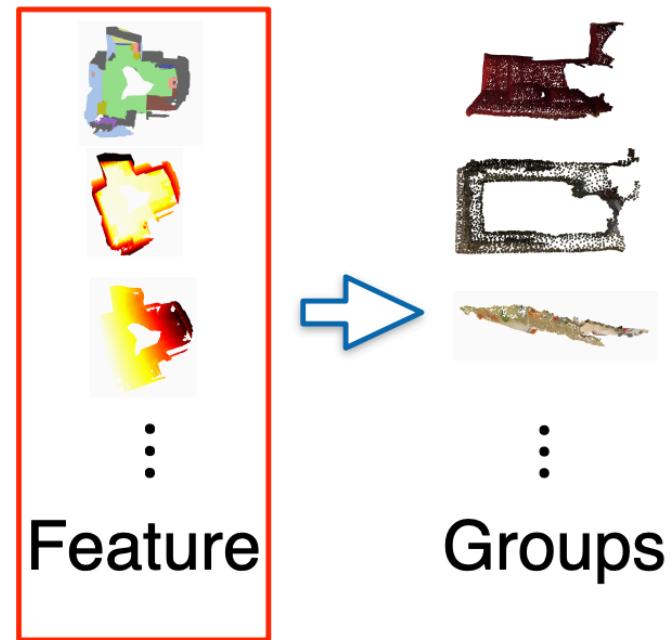
Review previous lectures

3D Instance Segmentation

Top-down Approaches



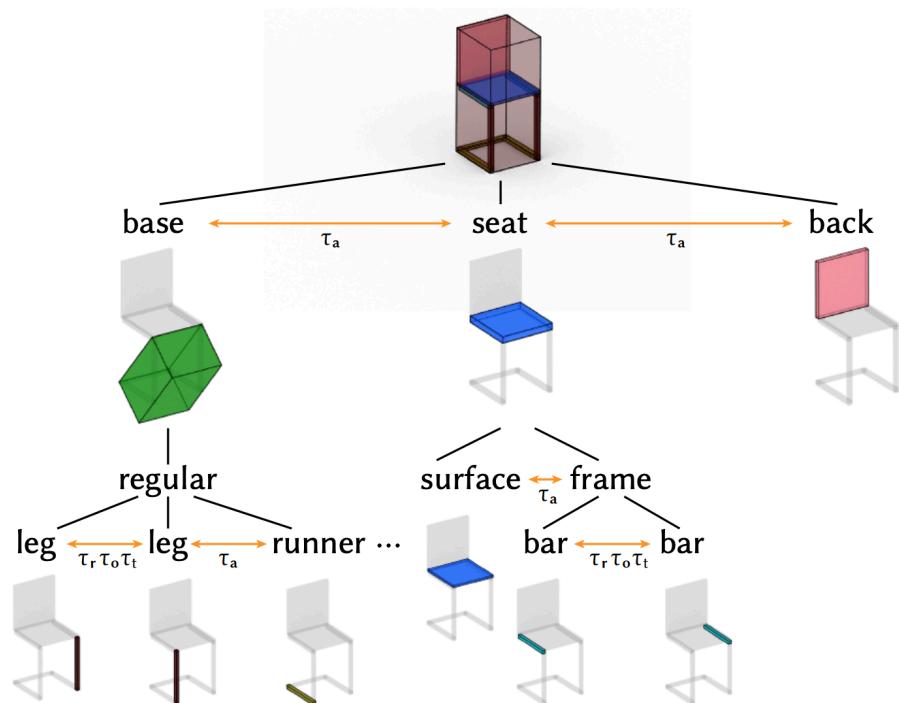
Bottom-up Approaches



But, is this done? Any differences between segmenting objects from scenes and segmenting parts from objects?

Part Instance Segmentation

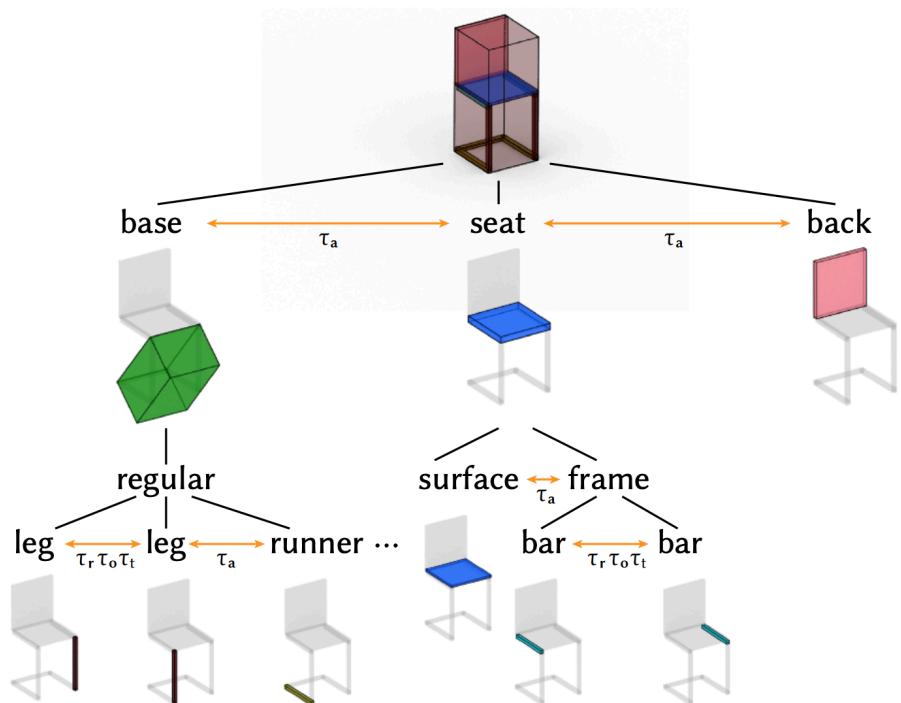
Shape parts have stronger relationships and structures



- Part Relationships hold (equal-length, symmetric)

Part Instance Segmentation

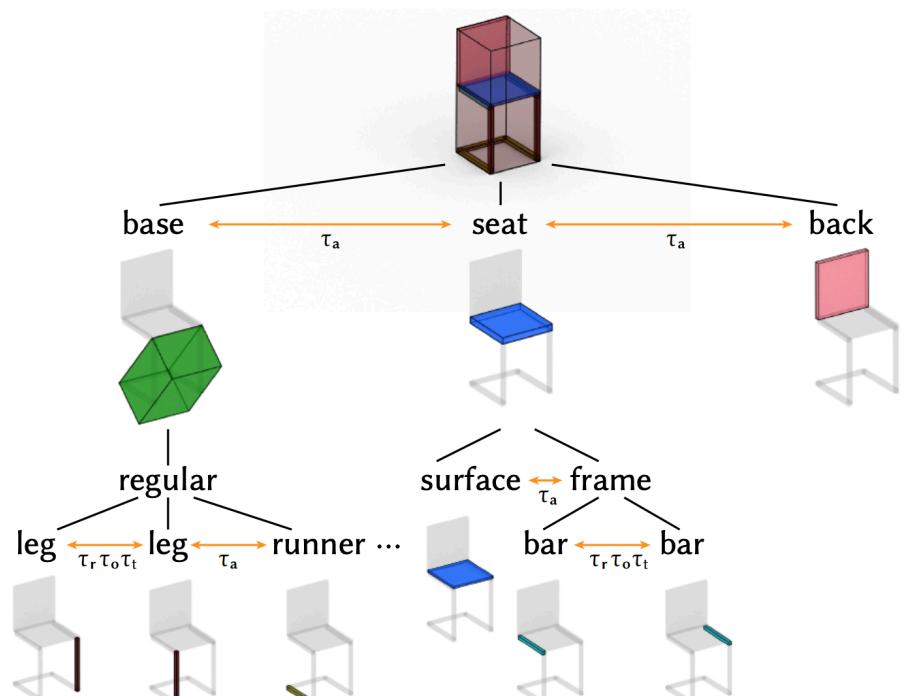
Shape parts have stronger relationships and structures



- Part Relationships hold (equal-length, symmetric)
- Part contexts matter to determine part labels (runners and bars have the same geometry)

Part Instance Segmentation

Shape parts have stronger relationships and structures



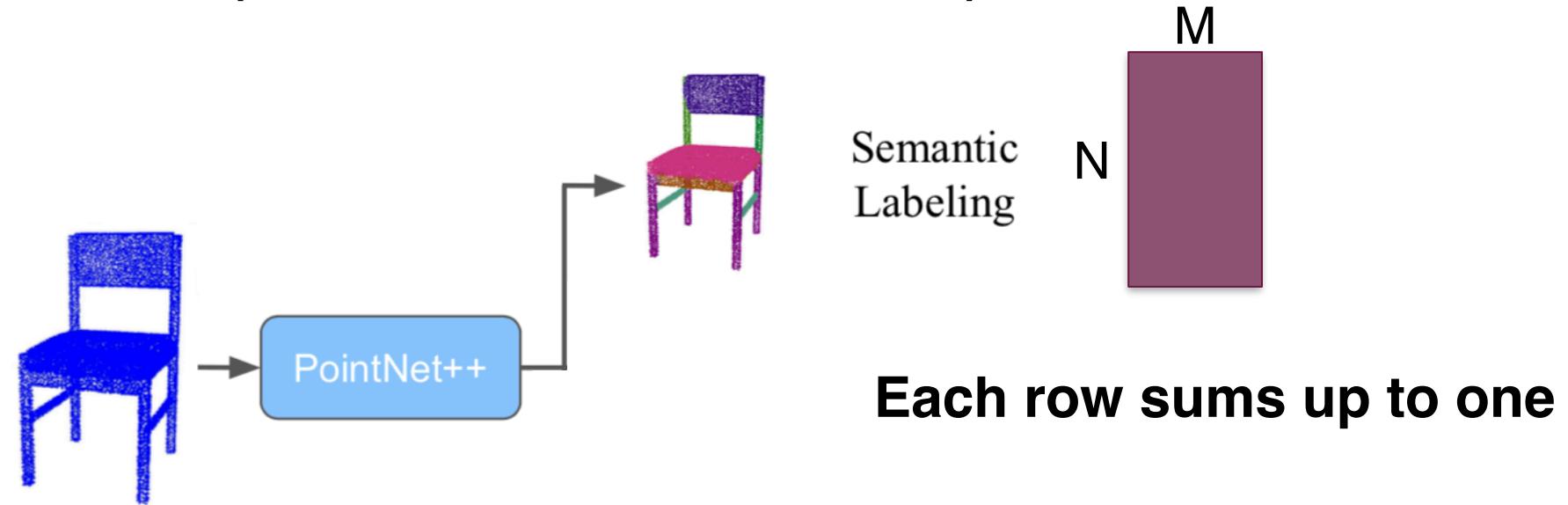
- Part Relationships hold (equal-length, symmetric)
- Part contexts matter to determine part labels (runners and bars have the same geometry)
- Panoptic Segmentation (explain all points)

Part Instance Segmentation

A simple network design effectively learns consistent part correspondences and overall shape structure

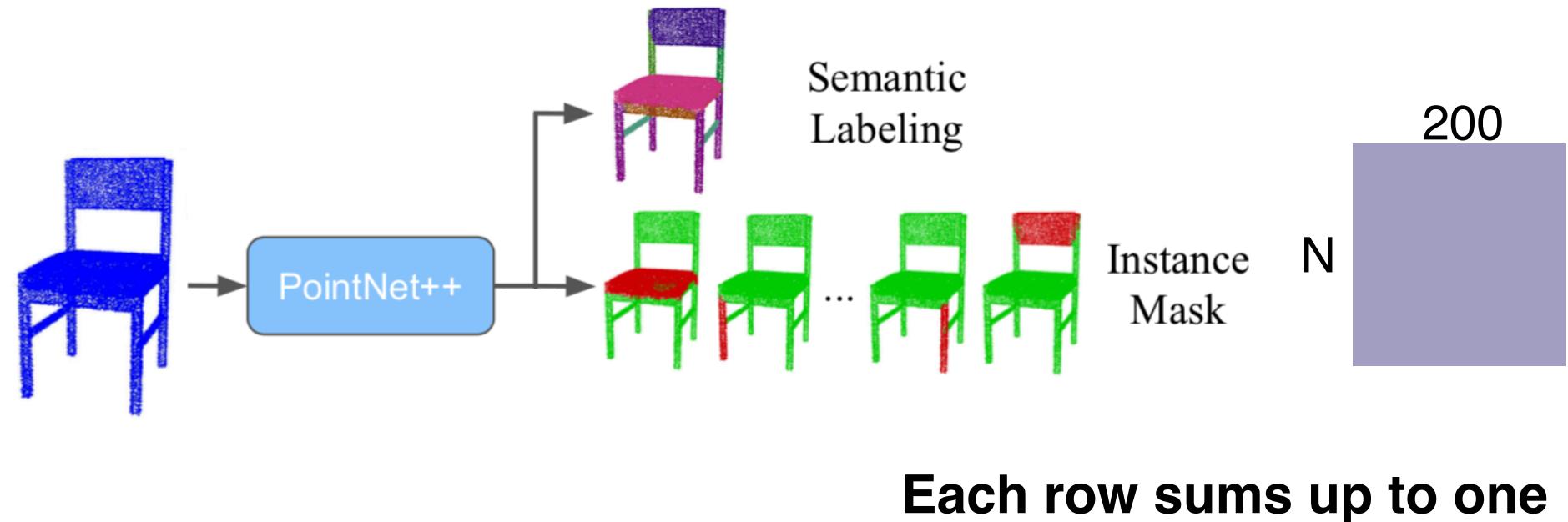
Part Instance Segmentation

A simple network design effectively learns consistent part correspondences and overall shape structure



Part Instance Segmentation

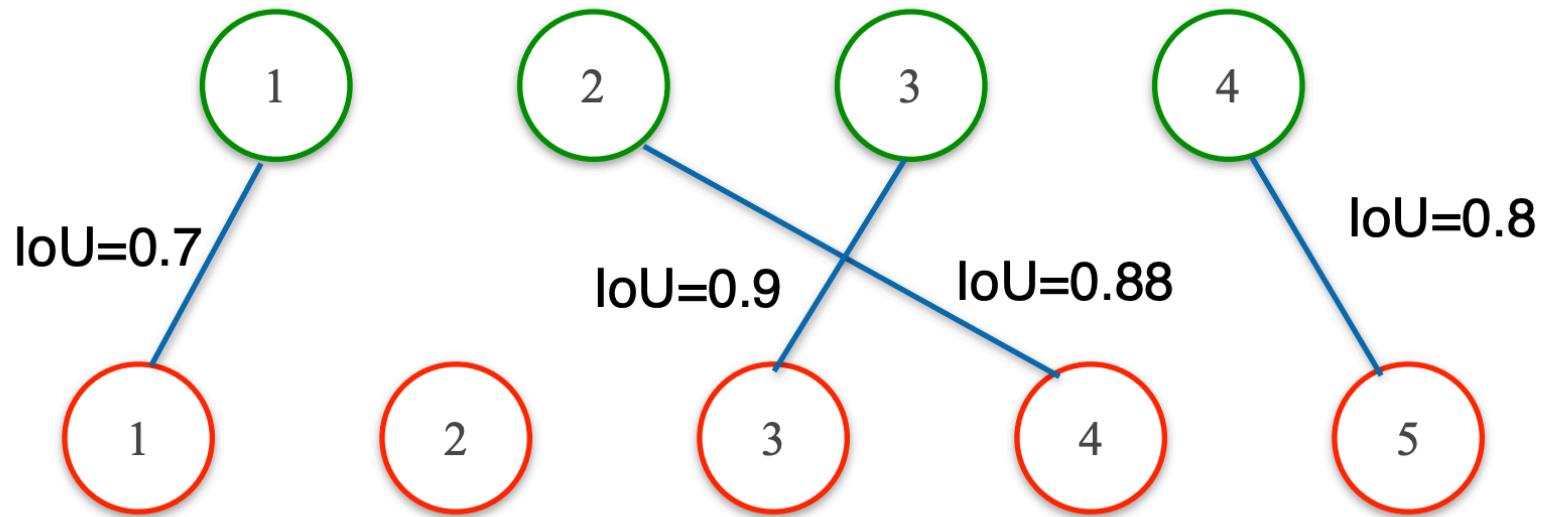
A simple network design effectively learns consistent part correspondences and overall shape structure



Mo et al., “PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding”, CVPR 2019

Optimal Association

- Objective: maximize the overall match gain
- Hungarian algorithm can solve this problem (similar to EMD)



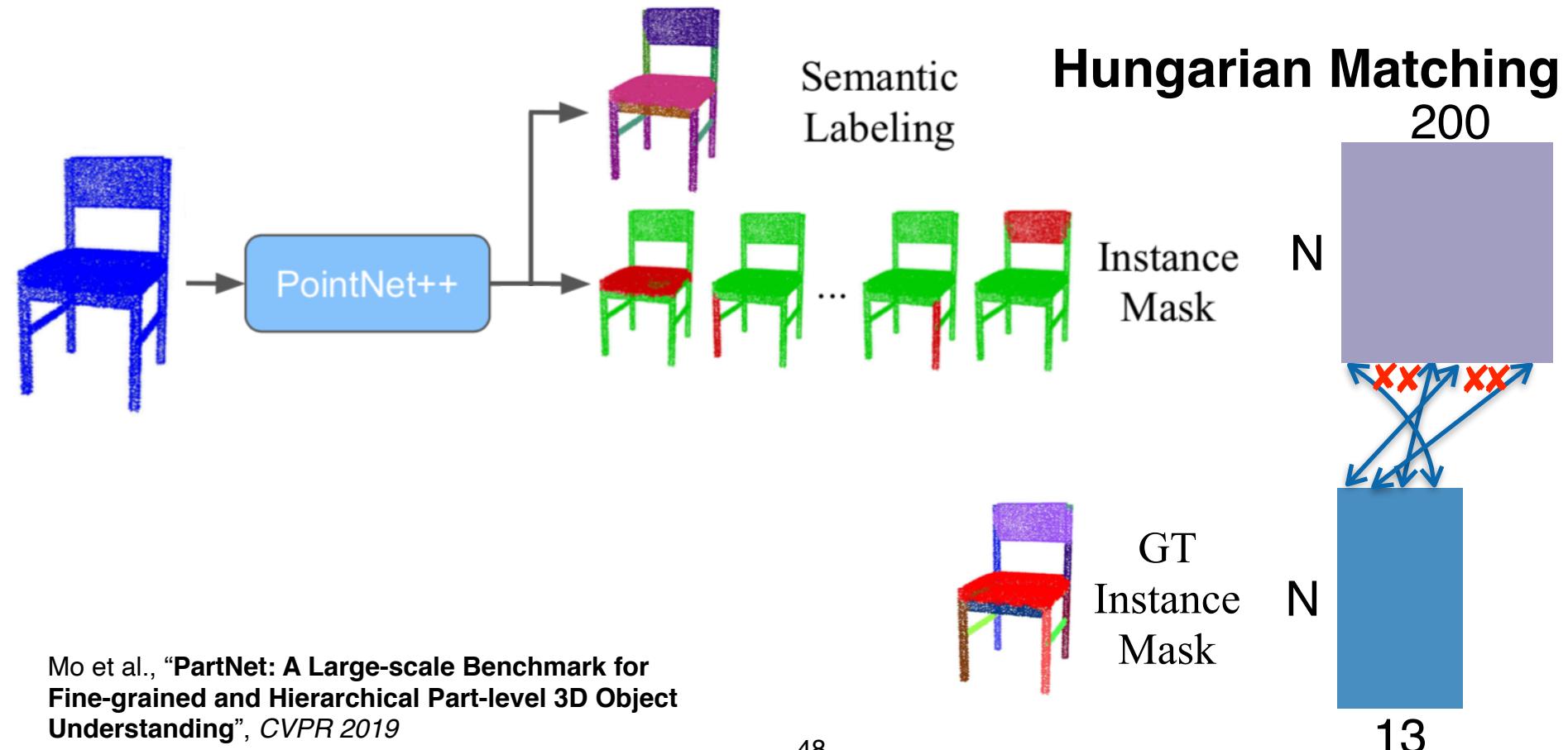
The overall gain is $0.7 + 0.9 + 0.88 + 0.8$

- Gain \Rightarrow cost, maximize \Rightarrow minimize

Review previous lectures

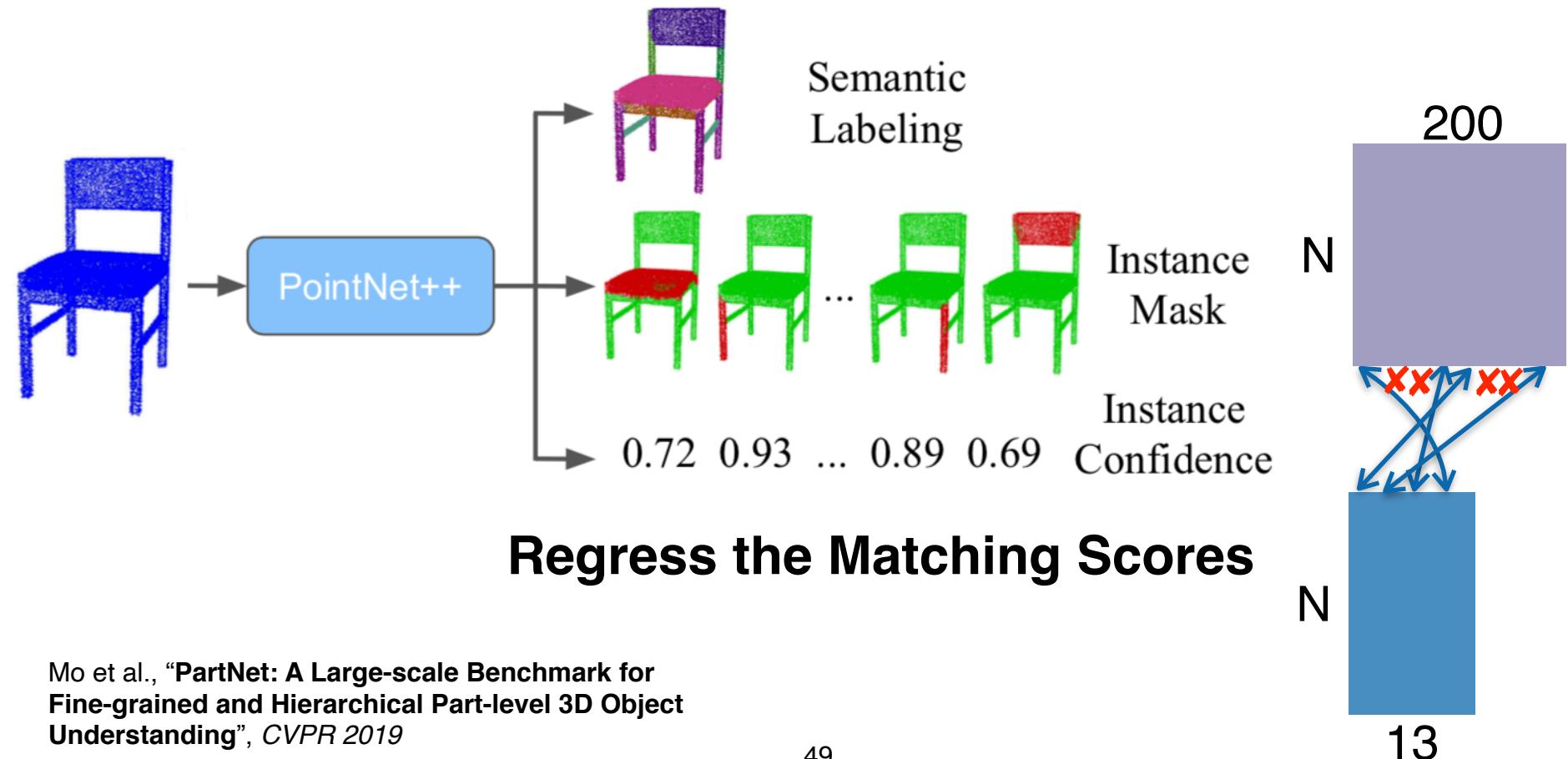
Part Instance Segmentation

A simple network design effectively learns consistent part correspondences and overall shape structure



Part Instance Segmentation

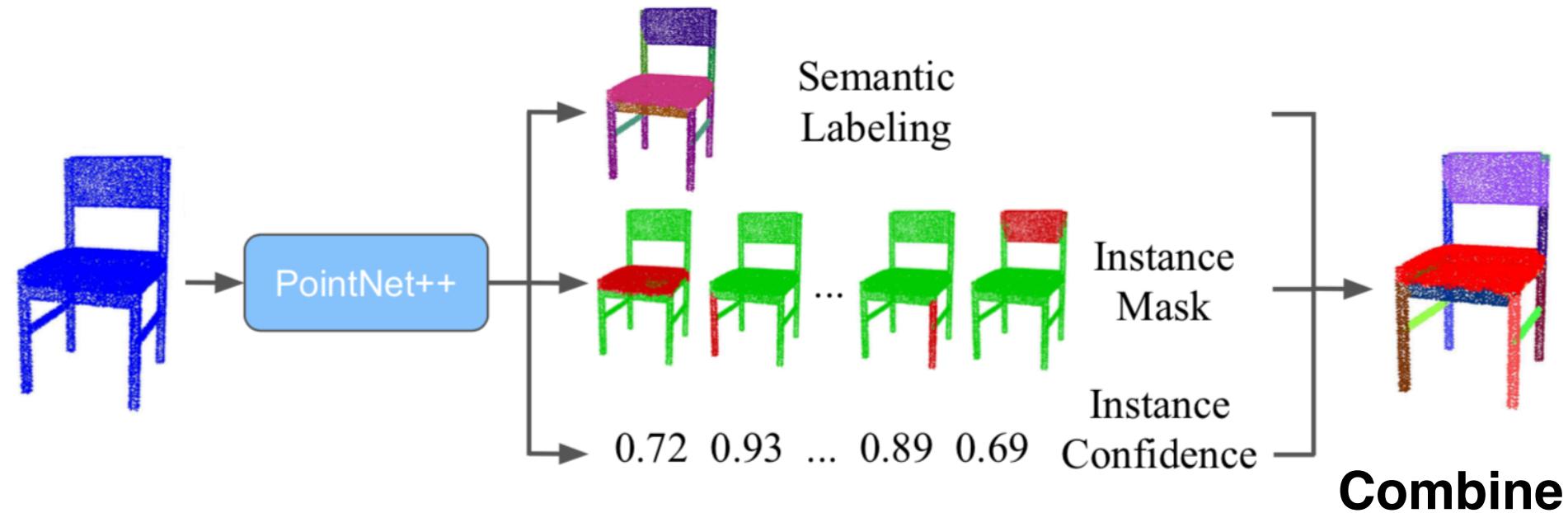
A simple network design effectively learns consistent part correspondences and overall shape structure



Mo et al., "PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding", CVPR 2019

Part Instance Segmentation

A simple network design effectively learns consistent part correspondences and overall shape structure



Mo et al., “PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding”, CVPR 2019

Part Instance Segmentation

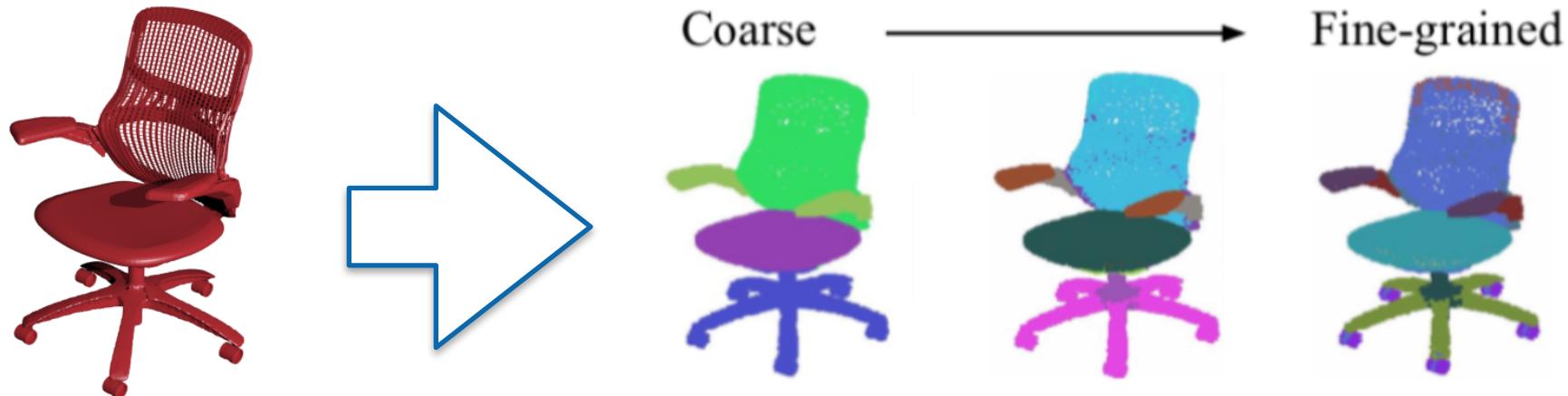
Simple network design effectively learns consistent part correspondences and overall shape structure



Same Color indicates Same Slot

Part Hierarchical Segmentation

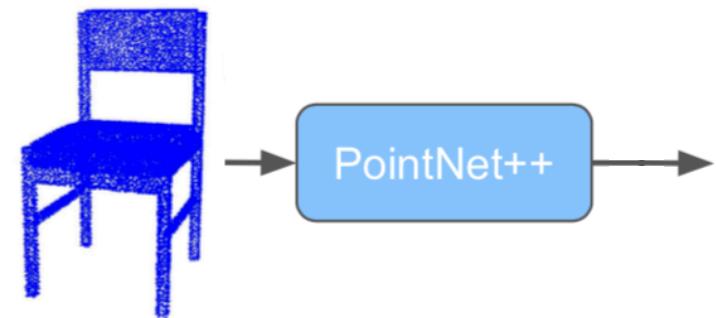
We segment parts at all levels and organize as a tree
(we do NOT know part tree structure for each shape)



How to tackle this task?

Part Hierarchical Segmentation

Pre-define slots in an instance-level part tree for all shapes in the category from the canonical AoG template

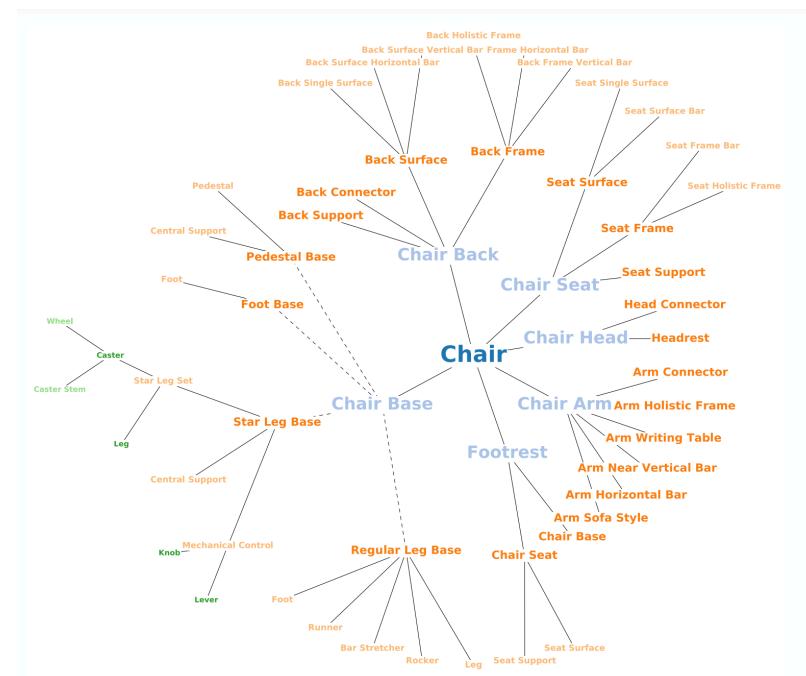
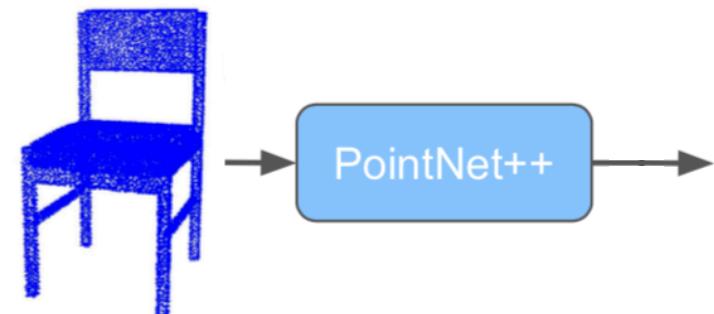


Mo et al., “PT2PC: Learning to Generate 3D Point Cloud Shapes from Part Tree Conditions”, *ECCV 2020*

Part Hierarchical Segmentation

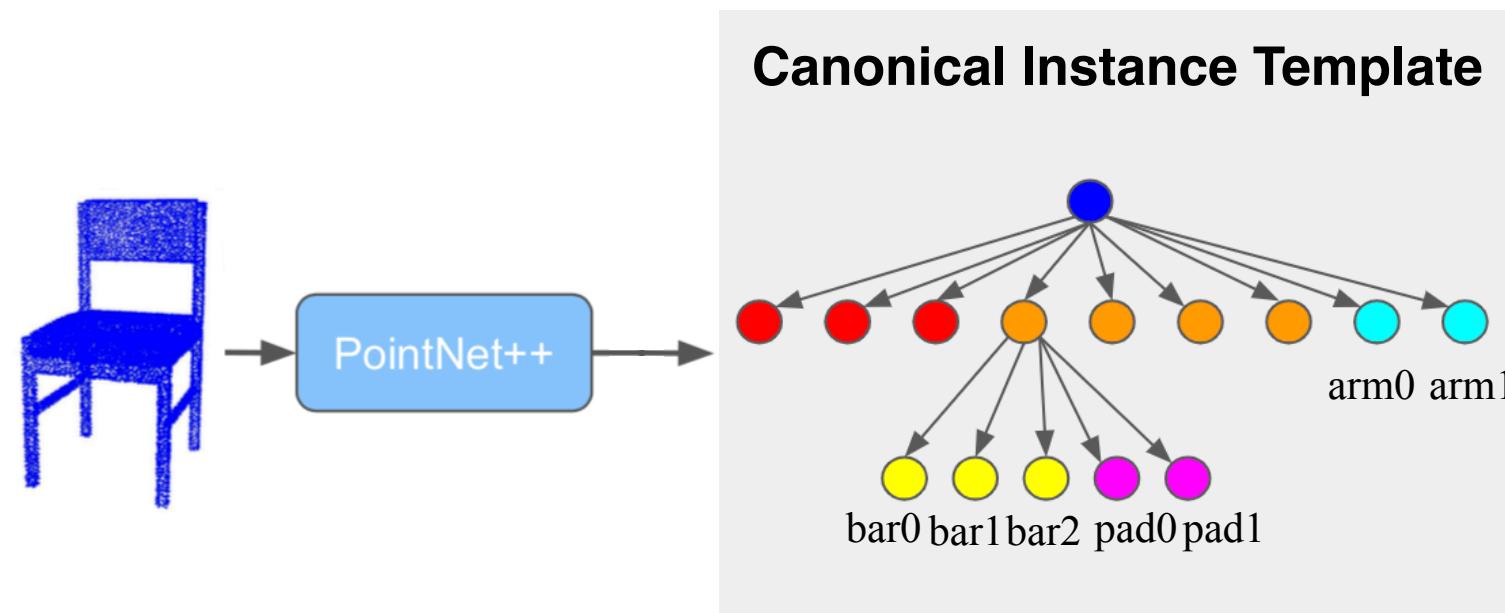
Pre-define slots in an instance-level part tree for all shapes in the category from the canonical AoG template

Canonical Semantics Template



Part Hierarchical Segmentation

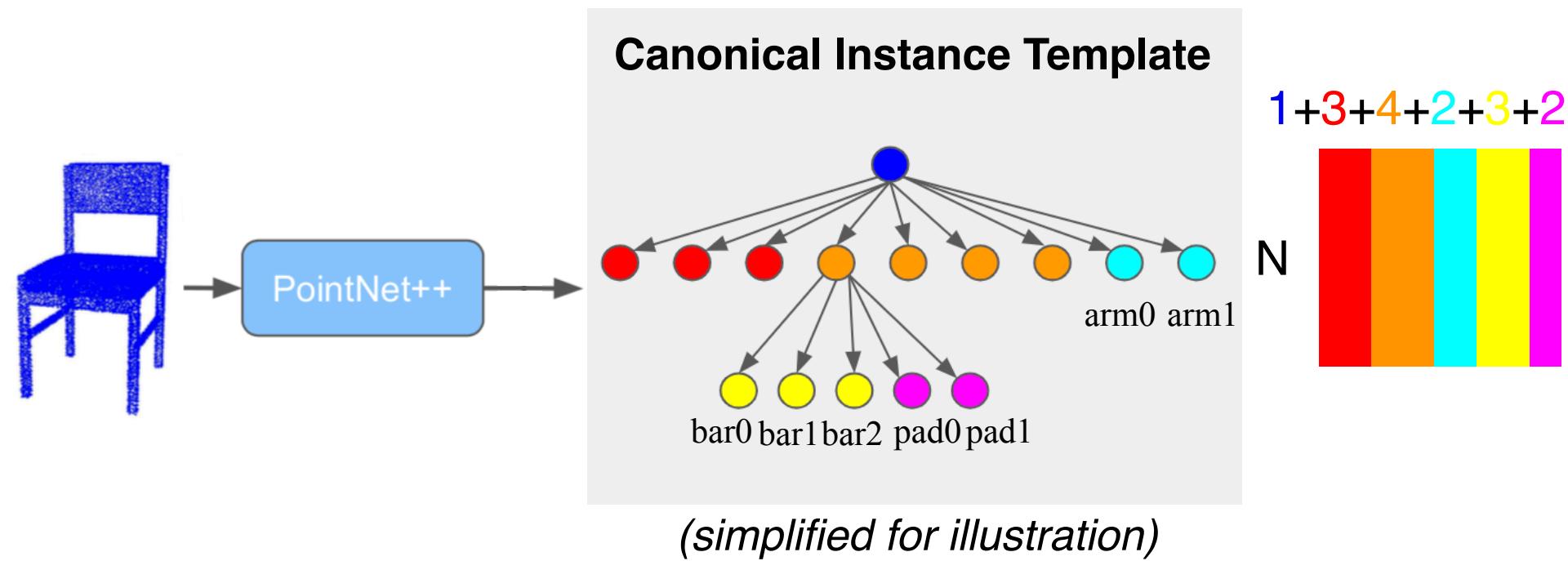
Pre-define slots in an instance-level part tree for all shapes in the category from the canonical AoG template



(simplified for illustration)

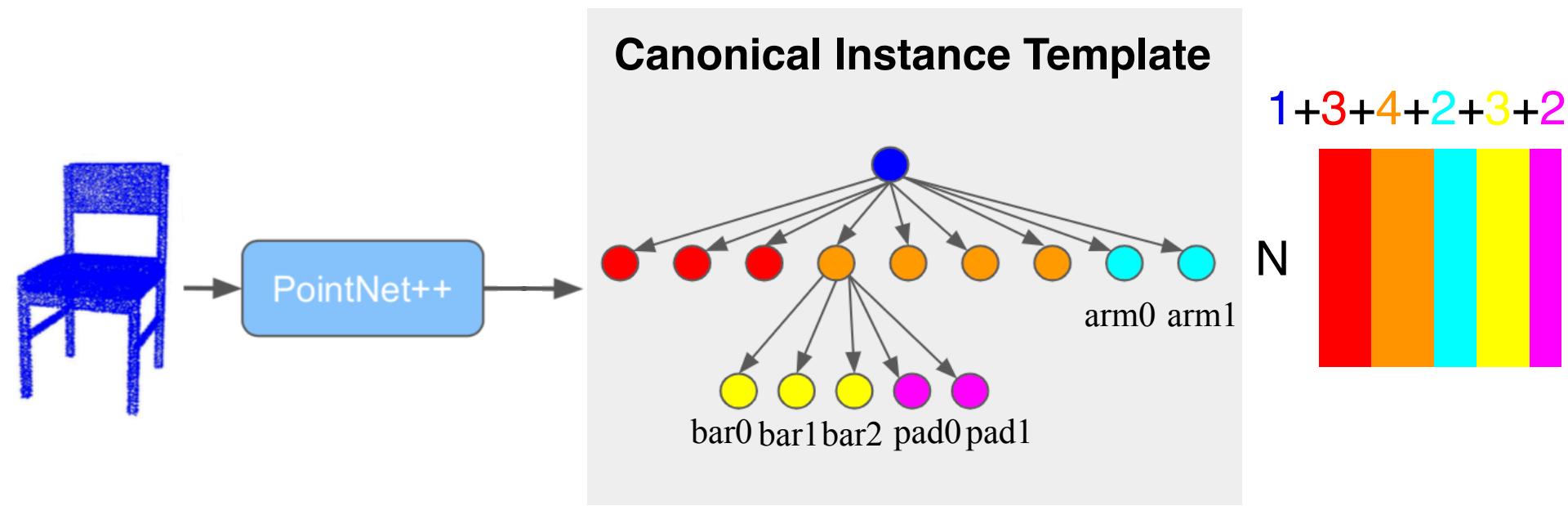
Part Hierarchical Segmentation

Pre-define slots in an instance-level part tree for all shapes in the category from the canonical AoG template



Part Hierarchical Segmentation

Pre-define slots in an instance-level part tree for all shapes in the category from the canonical AoG template



(simplified for illustration)

**Children Part
Masks sum up to
the Parent Mask**

Mo et al., "PT2PC: Learning to Generate 3D Point Cloud Shapes from Part Tree Conditions", ECCV 2020

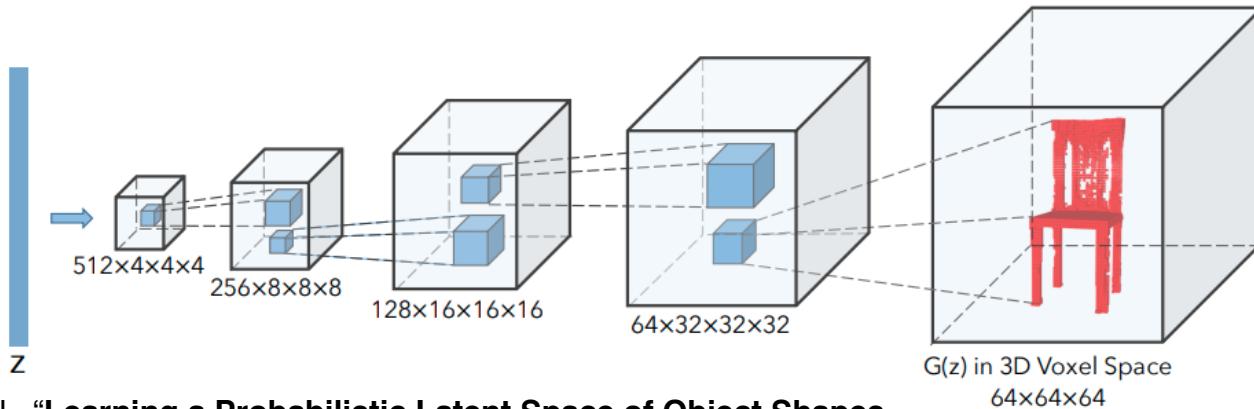
Summary

- Shape Part Segmentation and Scene Object Segmentation have different task properties
- Leverage strong Shape Structure Priors to learn better and more consistent part segmentation

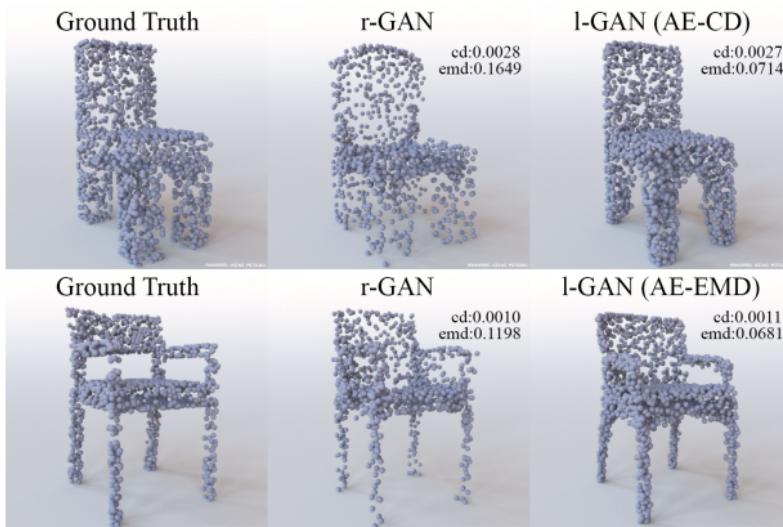
Part-based 3D Shape Generation

Semantic-level, Hierarchical, Part Connections

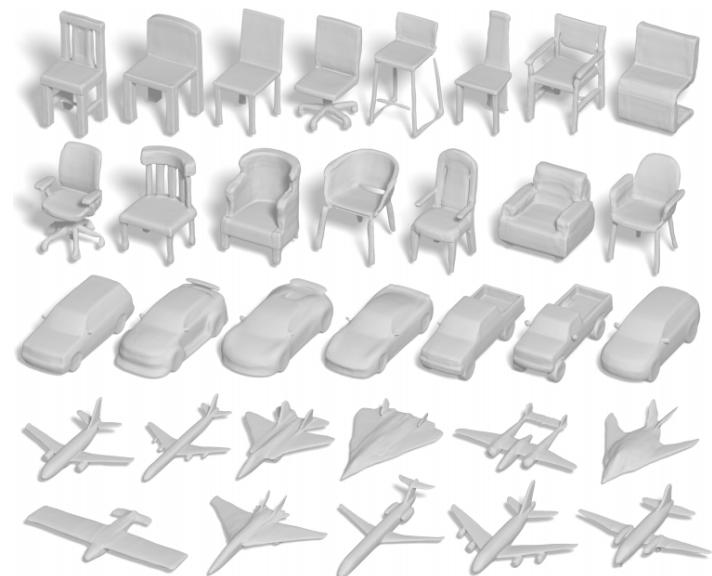
3D Shape Generation



Wu et al., “Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling”, *NeurIPS 2016*



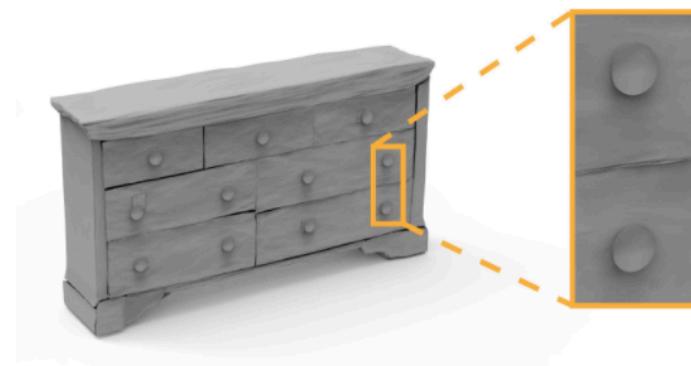
Achlioptas et al., “Learning Representations and Generative Models for 3D Point Clouds”, *ICML 2018*



Chen et al., “Learning Implicit Fields for Generative Shape Modeling”, *ICML 2019*

Part-based 3D Shape Generation

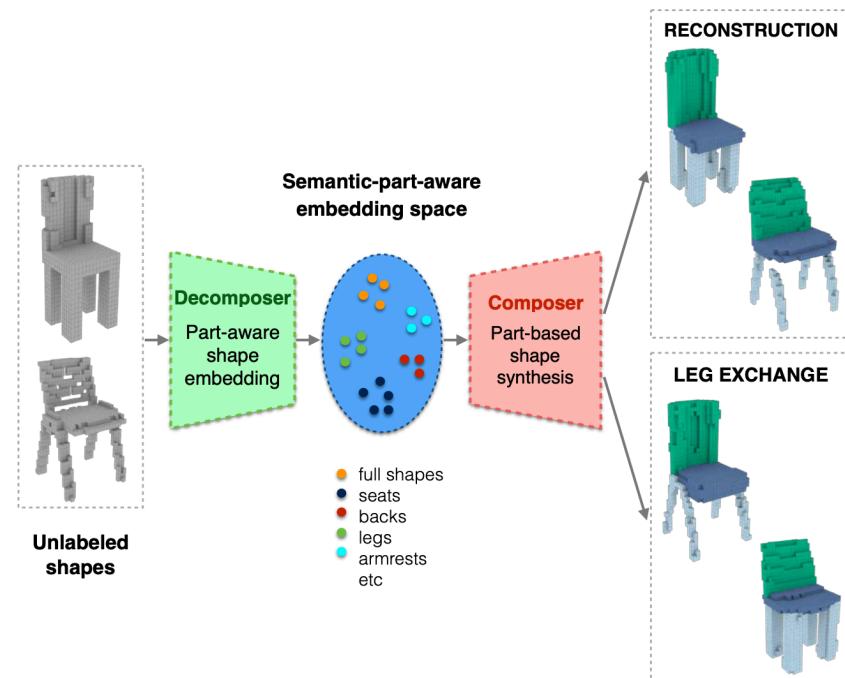
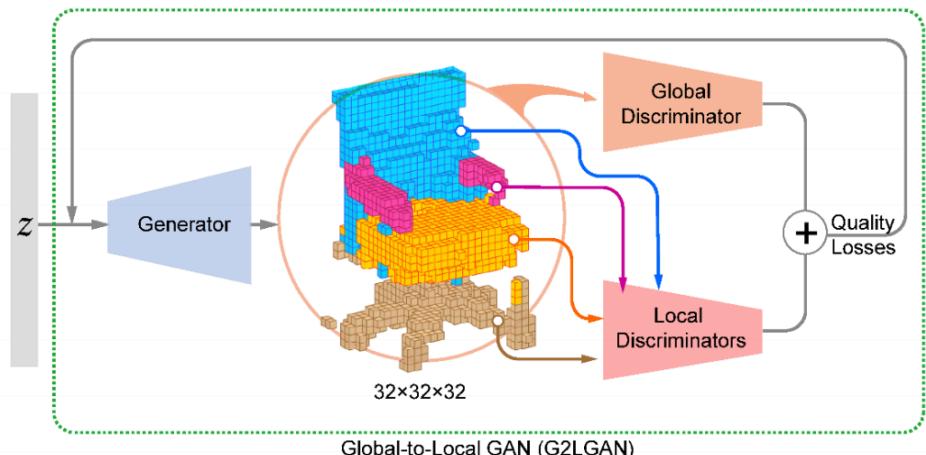
- Detailed Part Geometry
- Clear Shape Structures
- Sharp Part Boundaries
- With Semantic Part Labels



Yang and Mo et al., “**DSG-Net: Learning Disentangled Structure and Geometry for 3D Shape Generation**”, ACM ToG 2021

Semantic-level Synthesis and Assembly

Per-part Geometry Generation and Part Assembly

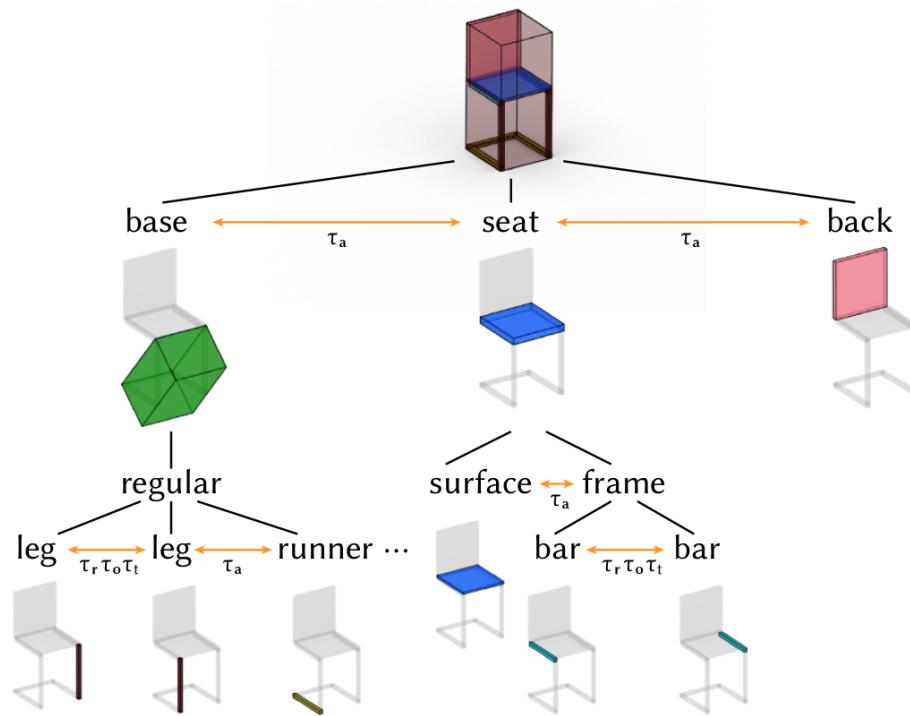


Wang and Schor et al., “**Global-to-Local Generative Model for 3D Shapes**”, Siggraph Asia 2018

Dubrovina et al., “**Composite Shape Modeling via Latent Space Factorization**”, ICCV 2019

Hierarchical Generation

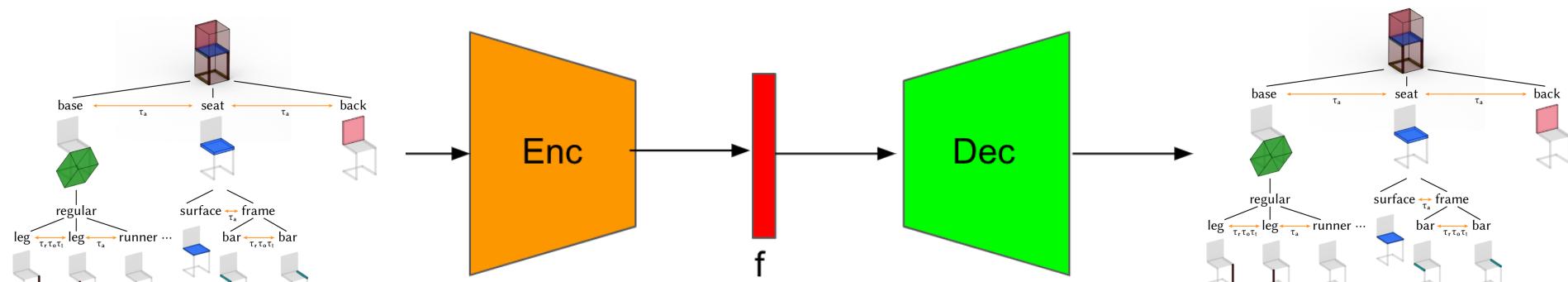
For fine-grained parts, we need coarse-to-fine generation



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, Siggraph Asia 2019

Hierarchical Generation

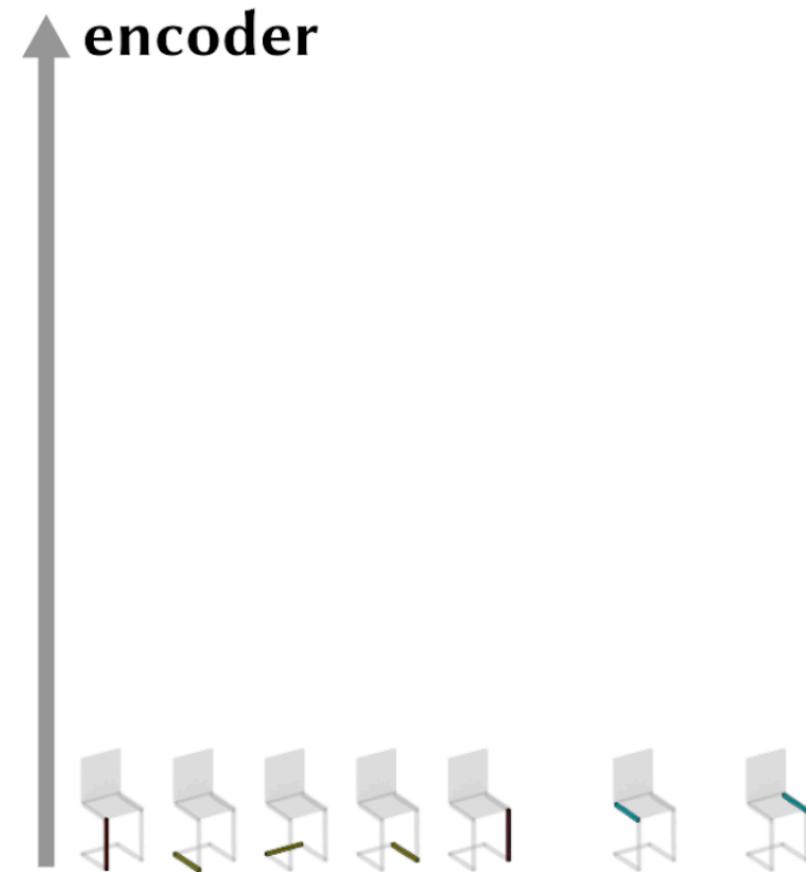
We use Variational Autoencoder (VAE)



$$f \sim N(0, I)$$

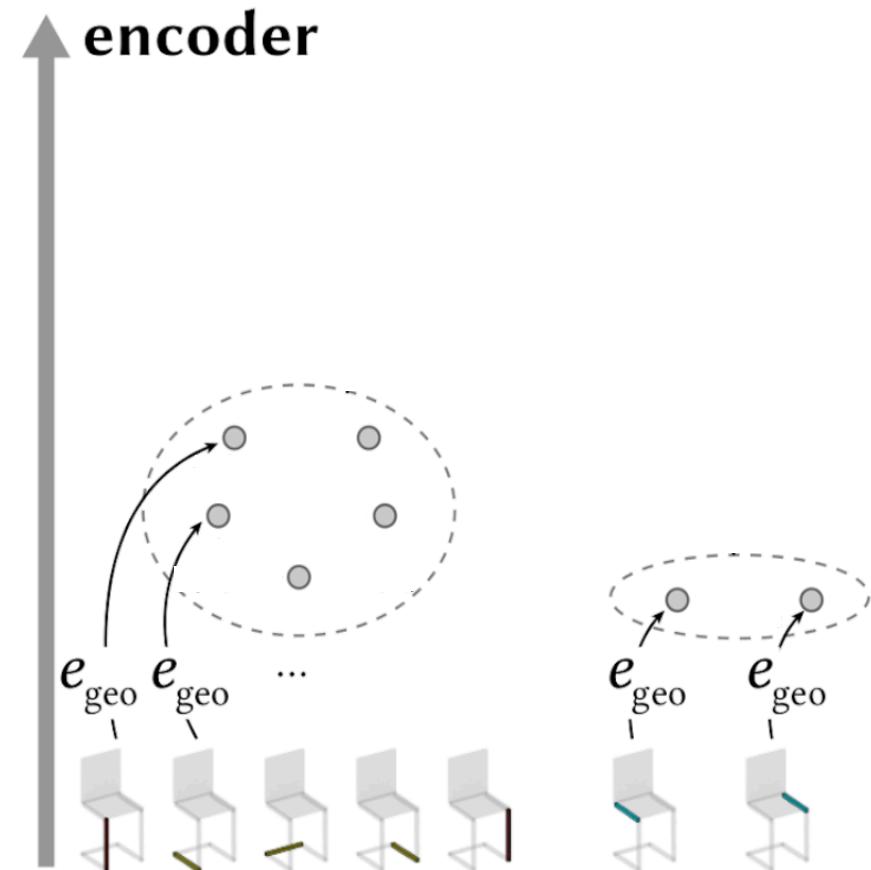
Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation



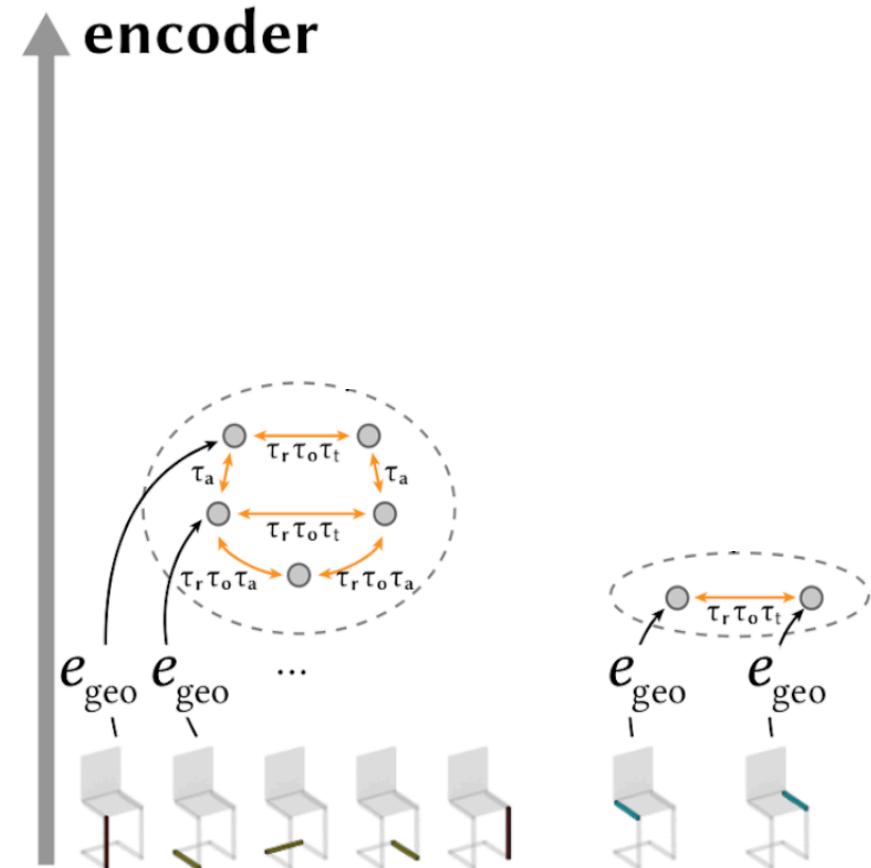
Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation



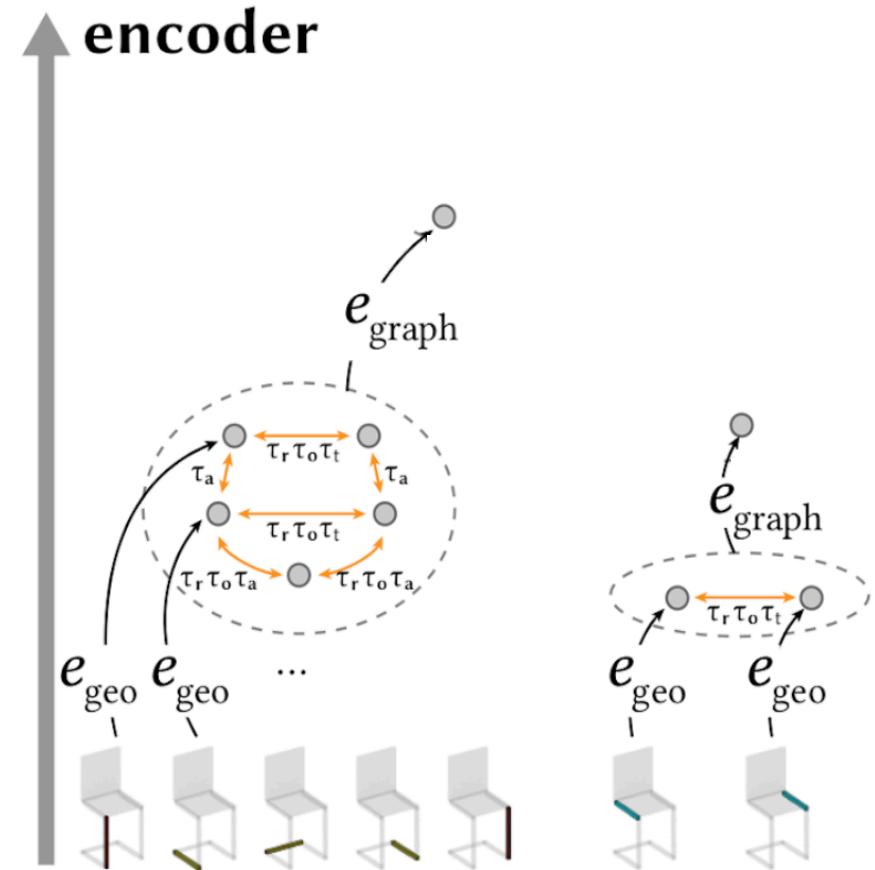
Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Hierarchical Generation



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

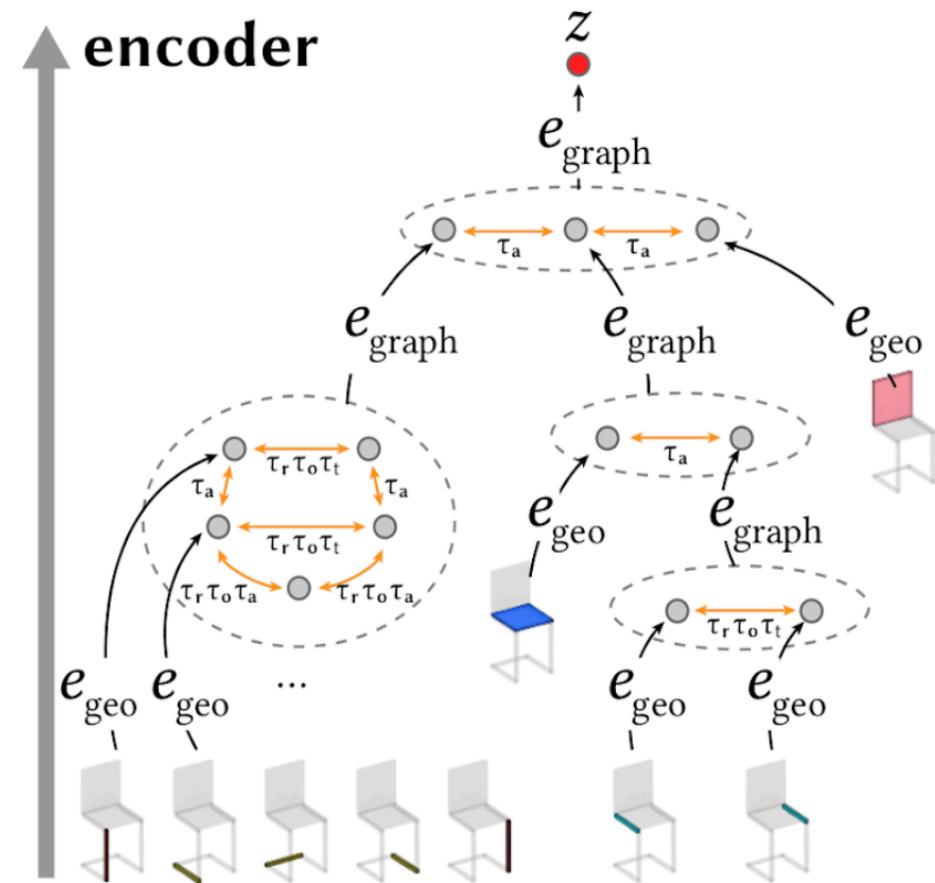
Hierarchical Generation



Graph Neural Network

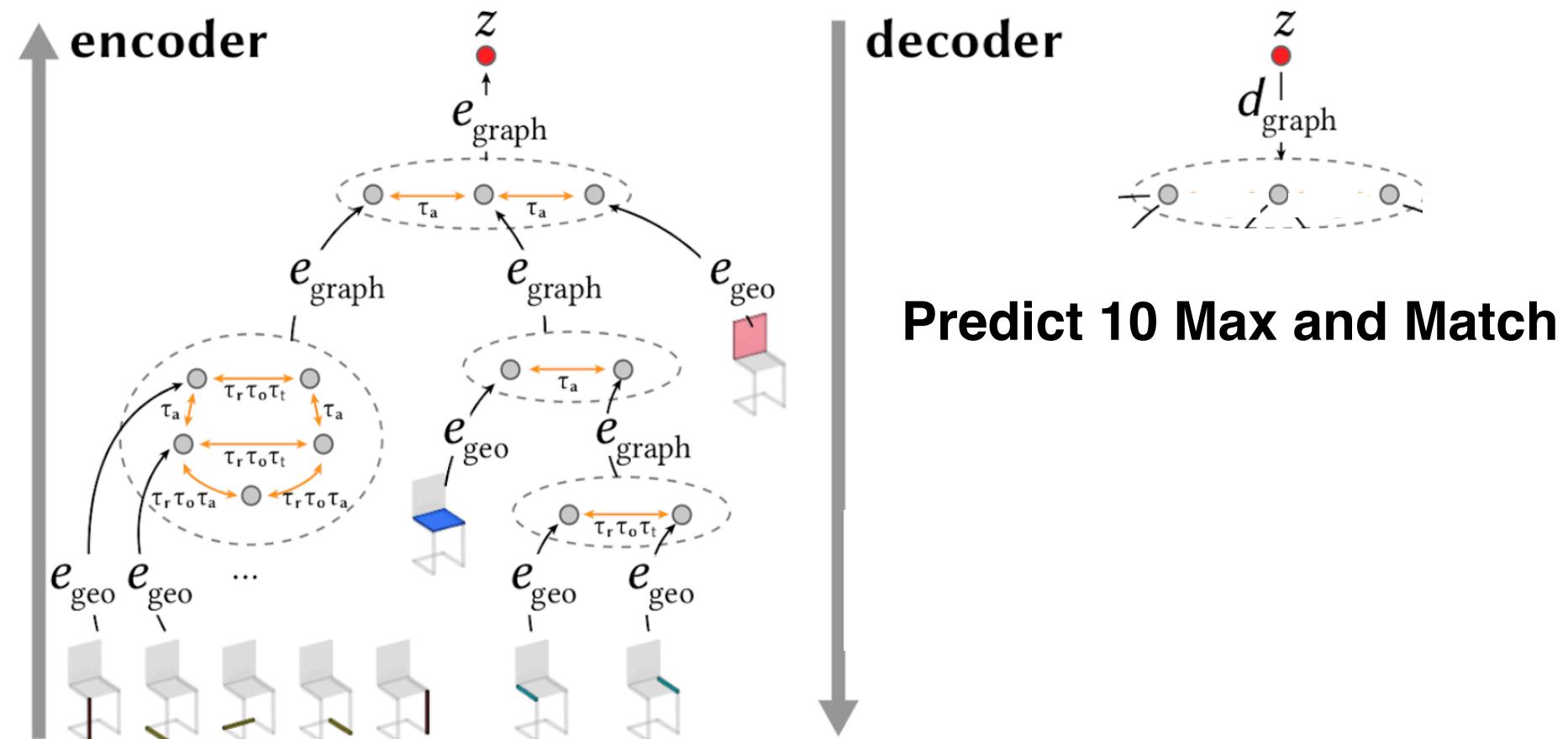
Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Hierarchical Generation



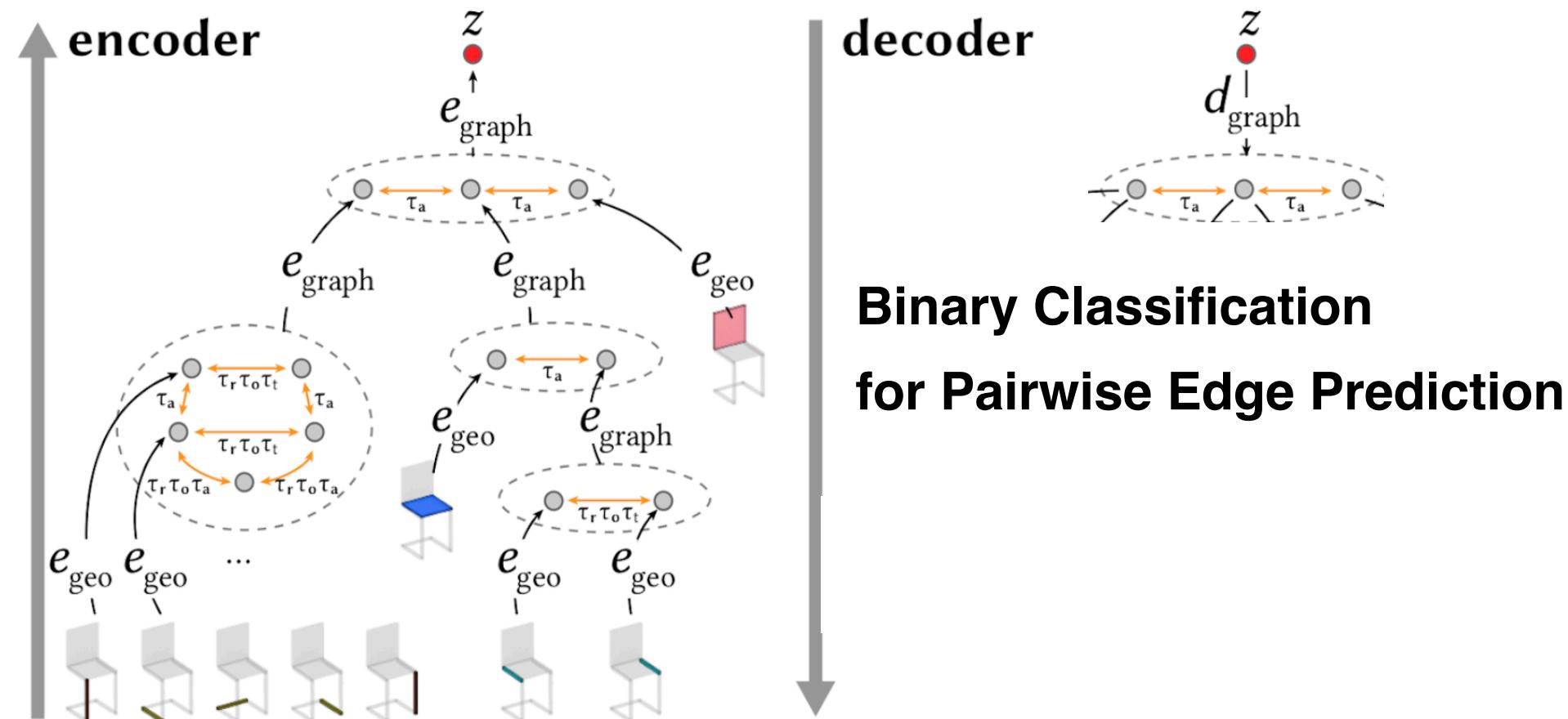
Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, Siggraph Asia 2019

Hierarchical Generation



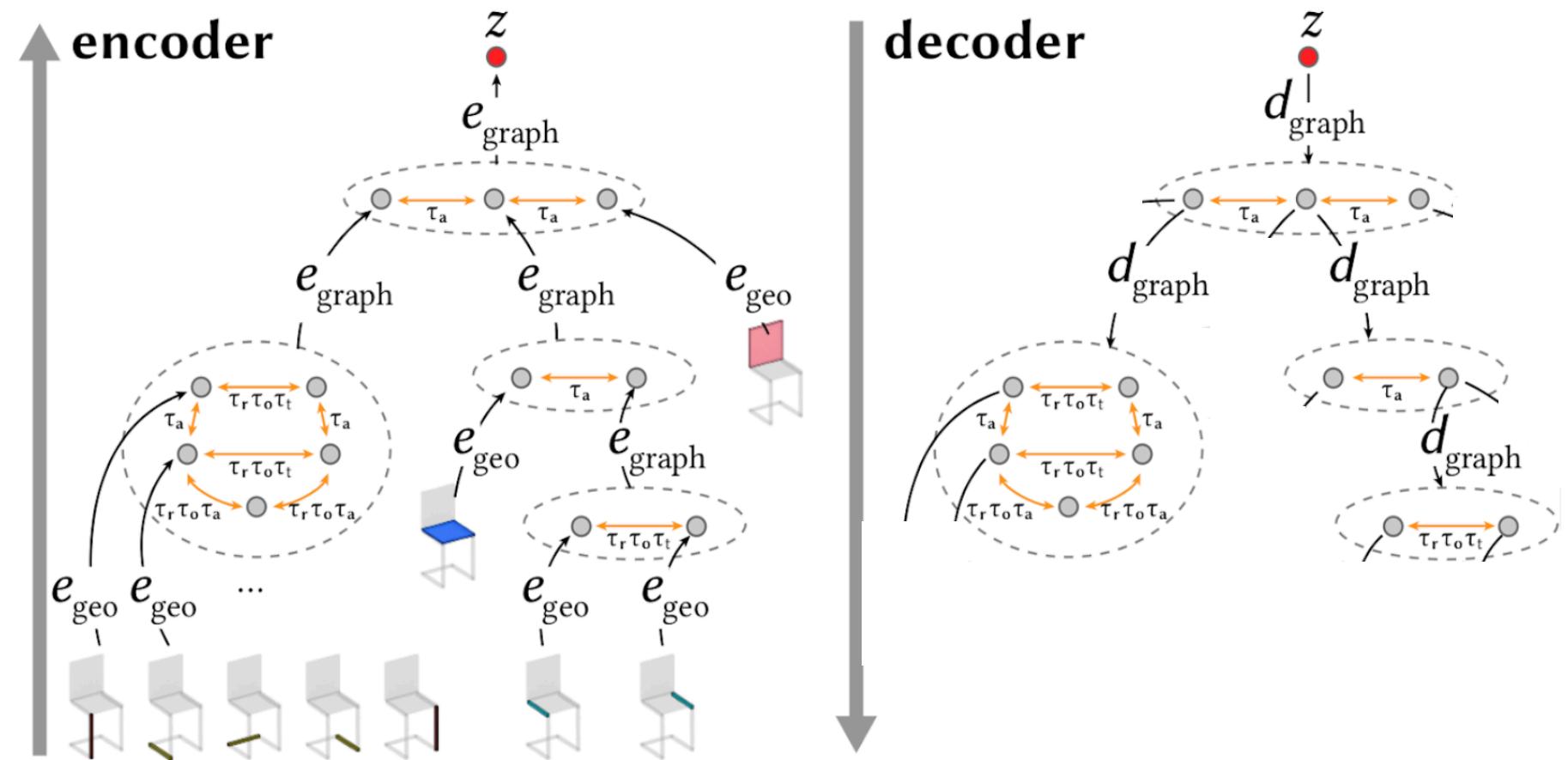
Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation



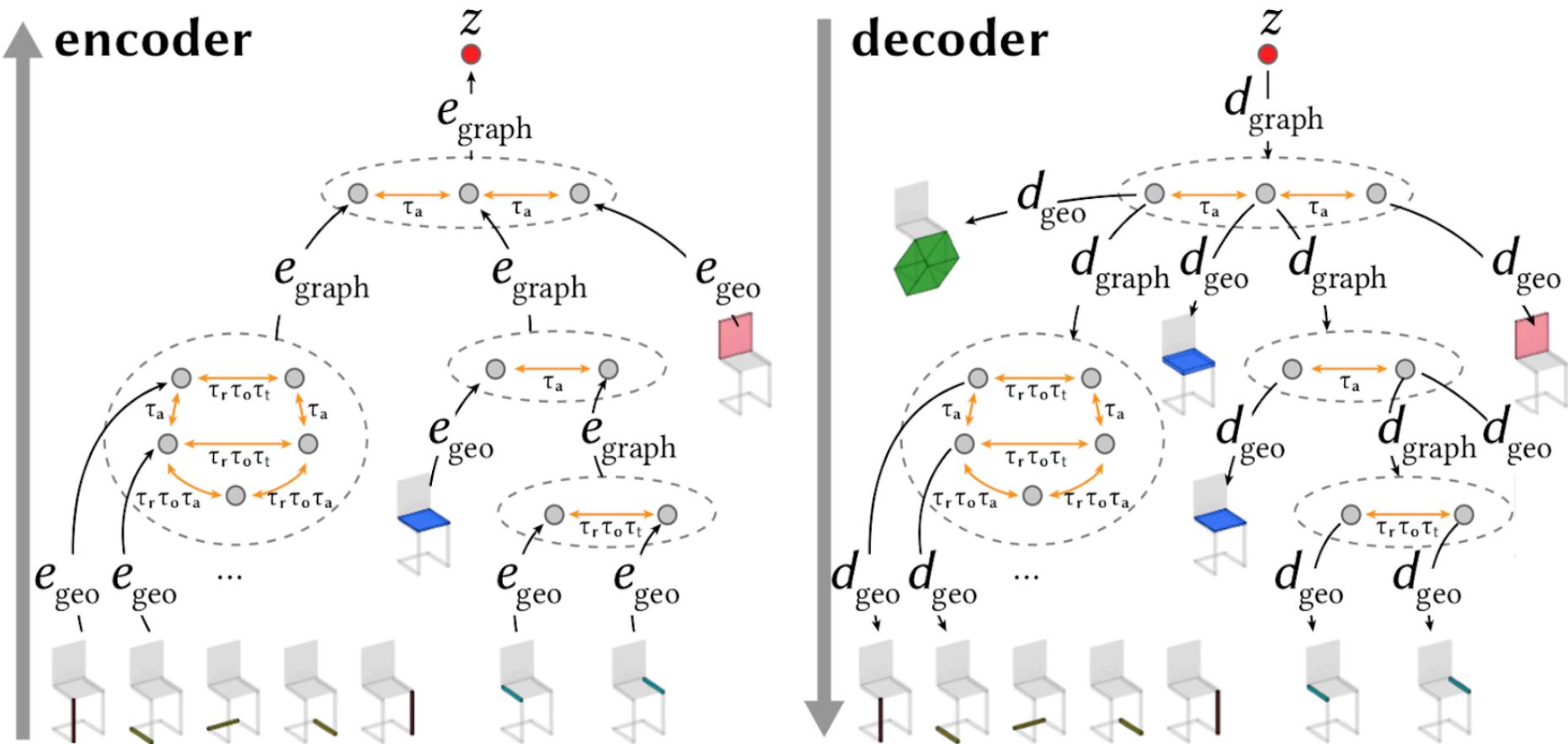
Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation



Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation



Recursive Neural Network

Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Hierarchical Generation: Results



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Hierarchical Generation: Results

Use mesh generation for leaf nodes



Yang and Mo et al., “**DSG-Net: Learning Disentangled Structure and Geometry for 3D Shape Generation**”, ACM ToG 2021

Hierarchical Generation: Results

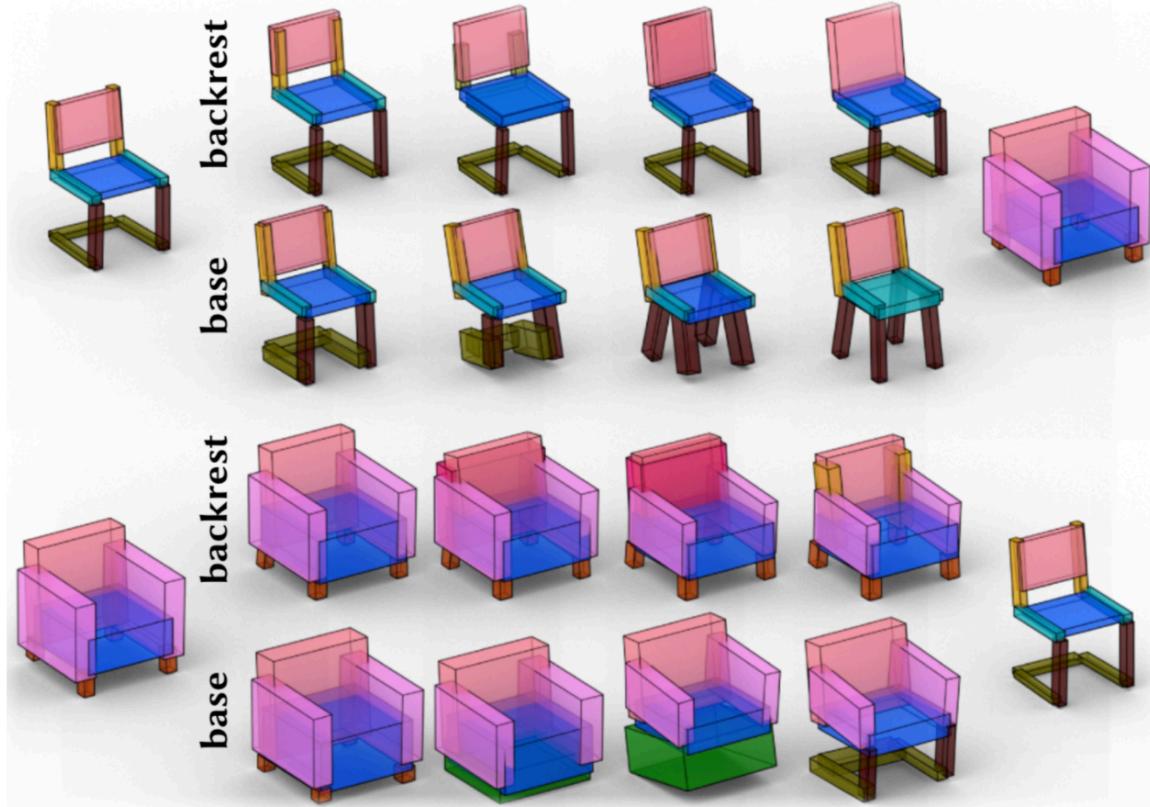
Image/Partial-scan to Shape Structure



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Hierarchical Generation: Results

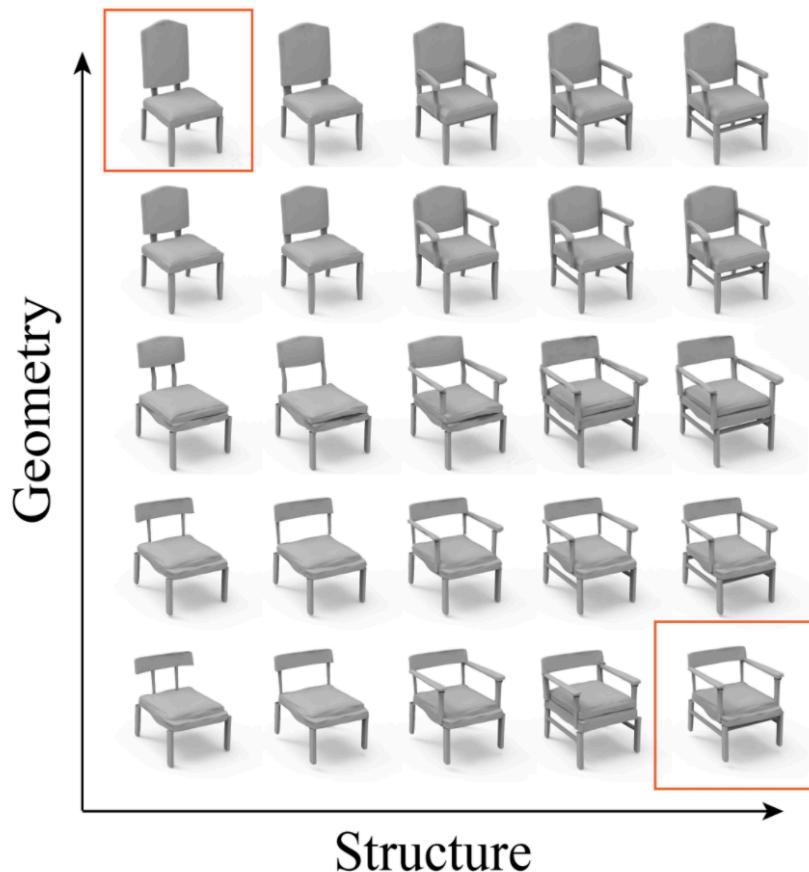
Controllable Part Interpolation



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Hierarchical Generation: Results

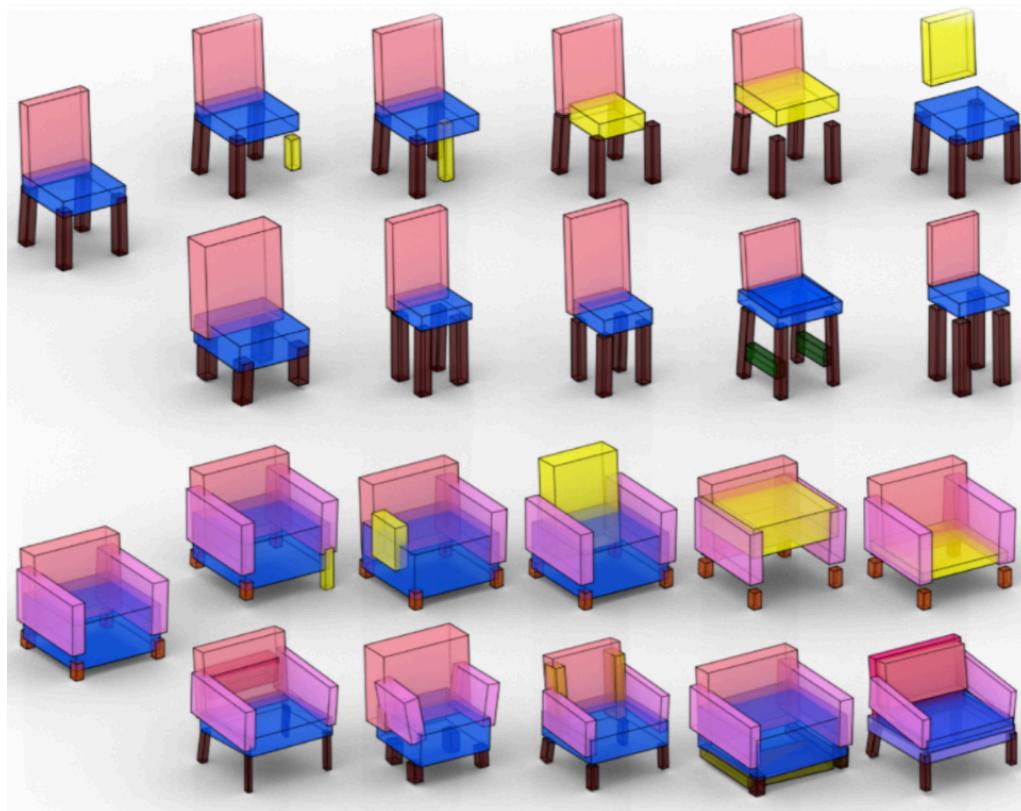
Disentangled Structure and Geometry Interpolation



Yang and Mo et al., “**DSG-Net: Learning Disentangled Structure and Geometry for 3D Shape Generation**”, ACM ToG 2021

Hierarchical Generation: Results

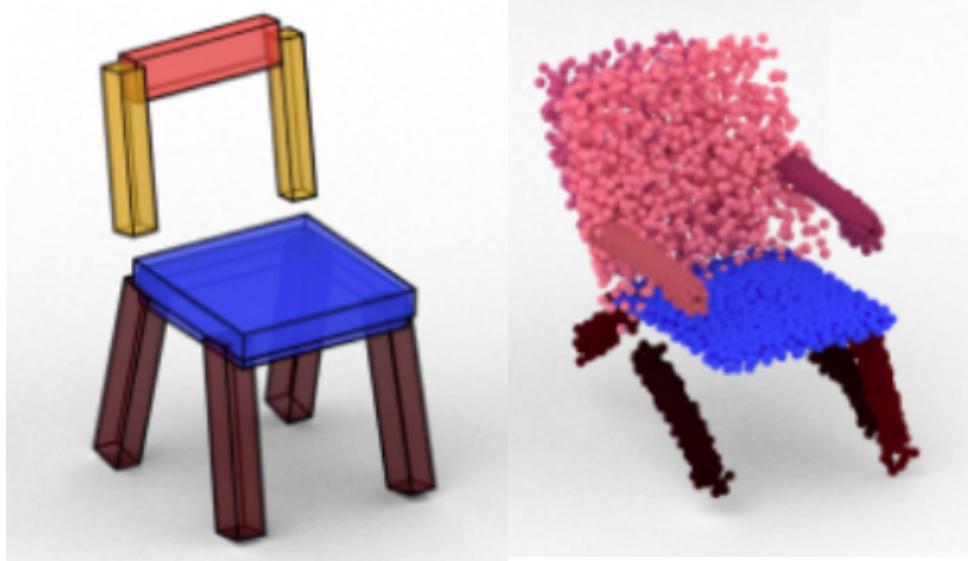
Shape Part Editing



Mo et al., “StructureNet: Hierarchical Graph Networks for 3D Shape Generation”, *Siggraph Asia 2019*

Part Connection Issue

There could be floating parts



Mo et al., “**StructureNet: Hierarchical Graph Networks for 3D Shape Generation**”, *Siggraph Asia 2019*

Part Connection Issue

Post-processing



Joint Re-synthesis



*Optimize part poses using
the predicted part
adjacency relationships*

Yang and Mo et al., “DSG-Net: Learning Disentangled Structure and Geometry for 3D Shape Generation”, ACM ToG 2021

*Erode the part connection
regions and re-generate
the local geometry*

Yin et al., “COALESCE: Component Assembly by Learning to Synthesize Connections”, 3DV 2020

Summary

- Per-part Synthesis and Assembly
- Hierarchical Generation for Fine-grained Geometry
- Need to deal with Part Connection Issue