三维物体建模中的形状结构表达与学习

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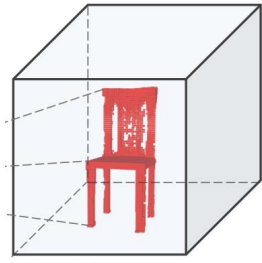
Geometric Deep Learning

Geometric Deep Learning

"A sofa chair with thin handles"
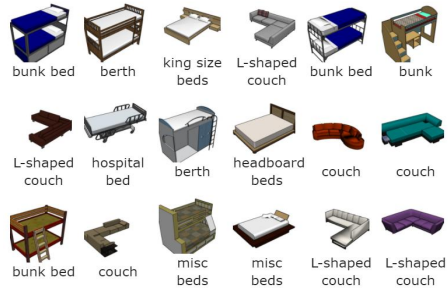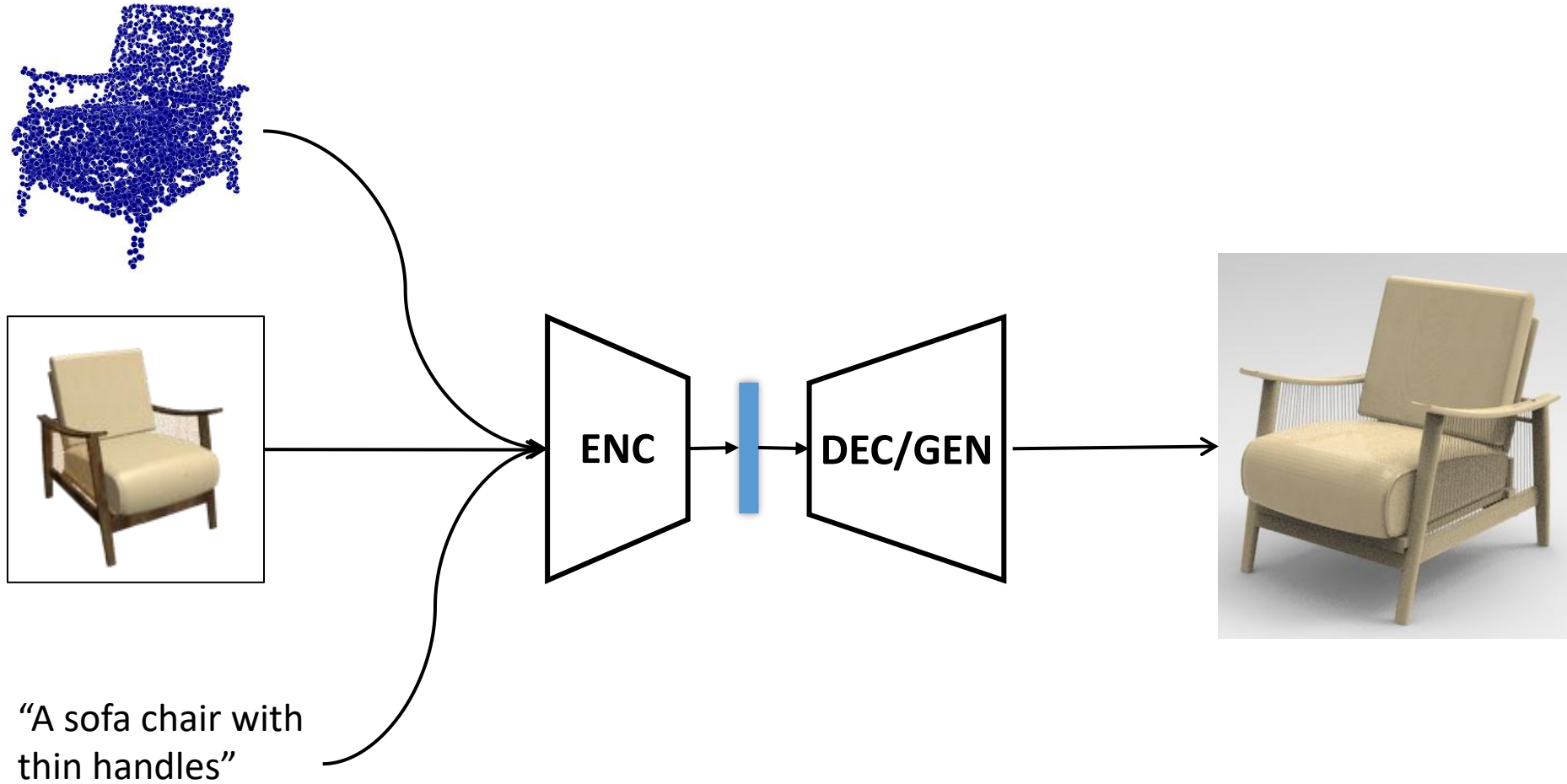
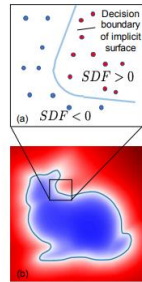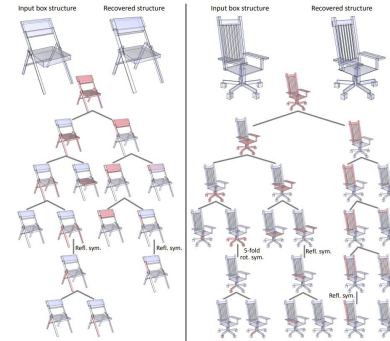# Many Different 3D Representations...
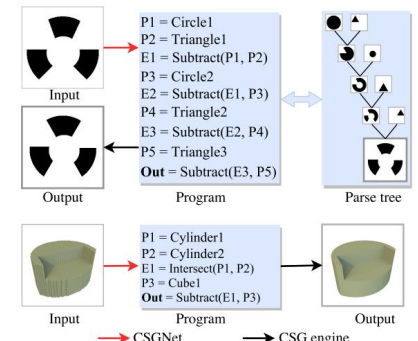
[3DGAN NIPS 2016]

[AtlasNet CVPR 2018]
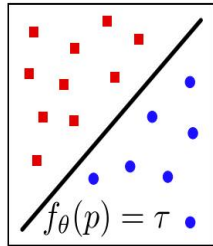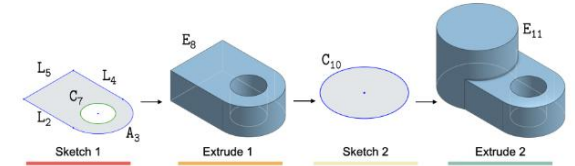
[OccNet CVPR 2019]

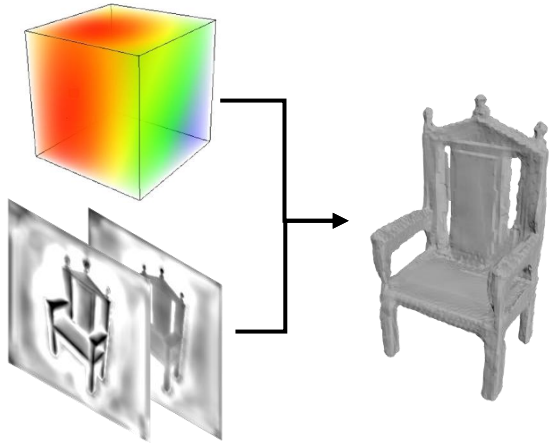[DeepSDF CVPR 2019]

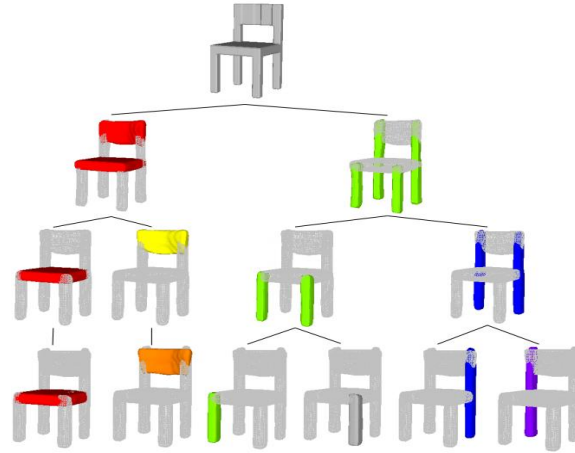[GRASS Siggraph 2017]

[CSGNET CVPR 2018]

[BSP-Net CVPR 2020]

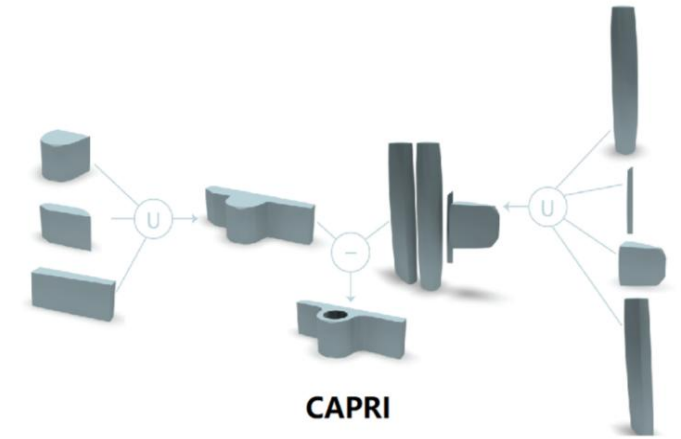[DeepCAD ICCV 2021]

Outline

**Detail Disentangled
Implicit Field**
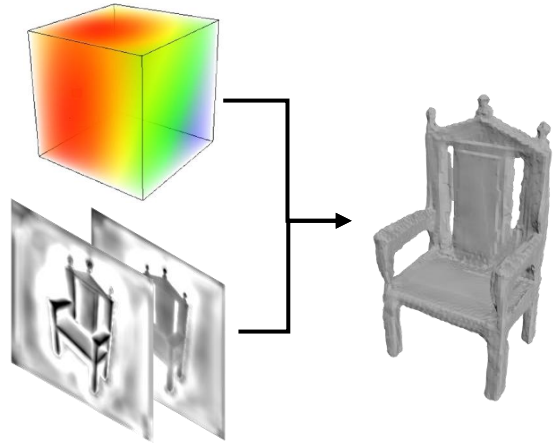
**Recursive
Implicit Field**

**Compact
CSG Representation**

Which 3D representation? **How** to learn (unsupervisedly)?

Outline

Detail Disentangled Implicit Field
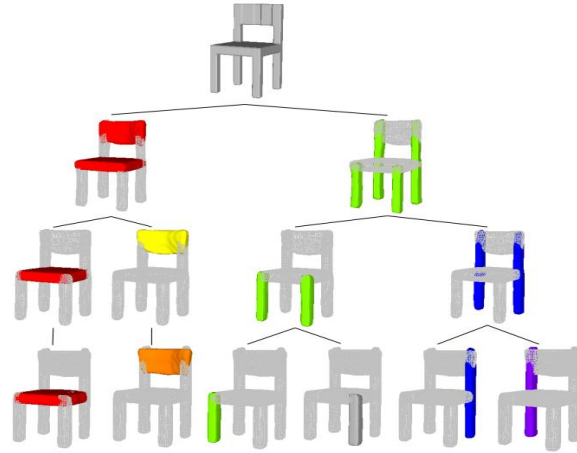
Recursive Implicit Field
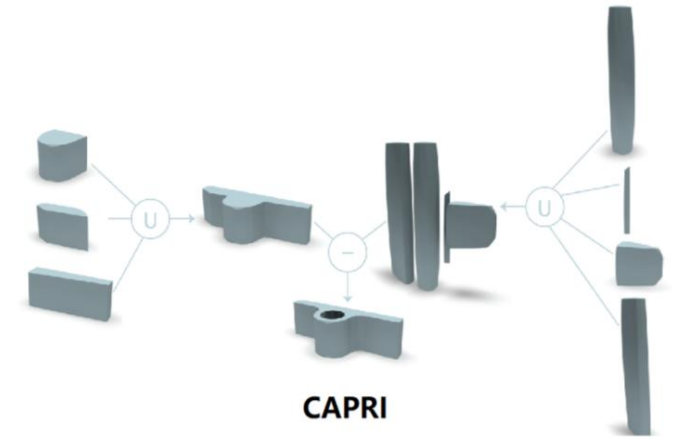
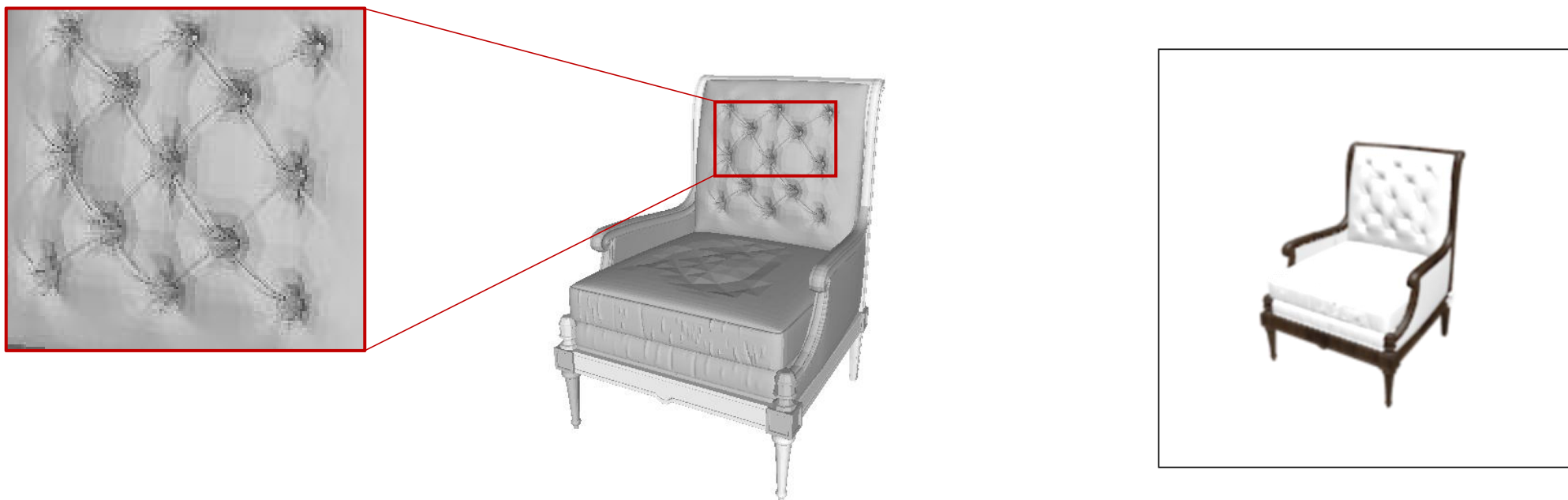**Compact CSG Representation**

1. Detail Disentangled Implicit Field

The shape details are (1) distinctive for each shape, and
(2) hard to measure, (3) visible from images.

1. Detail Disentangled Implicit Field

Base field   Front map   Back map   =

1. Detail Disentangled Implicit Field

Base field   Front map   Back map

1. Detail Disentangled Implicit Field

Base field + Front map + Back map =

Laplacian constraint   As small-scale as possible   SDF fusion
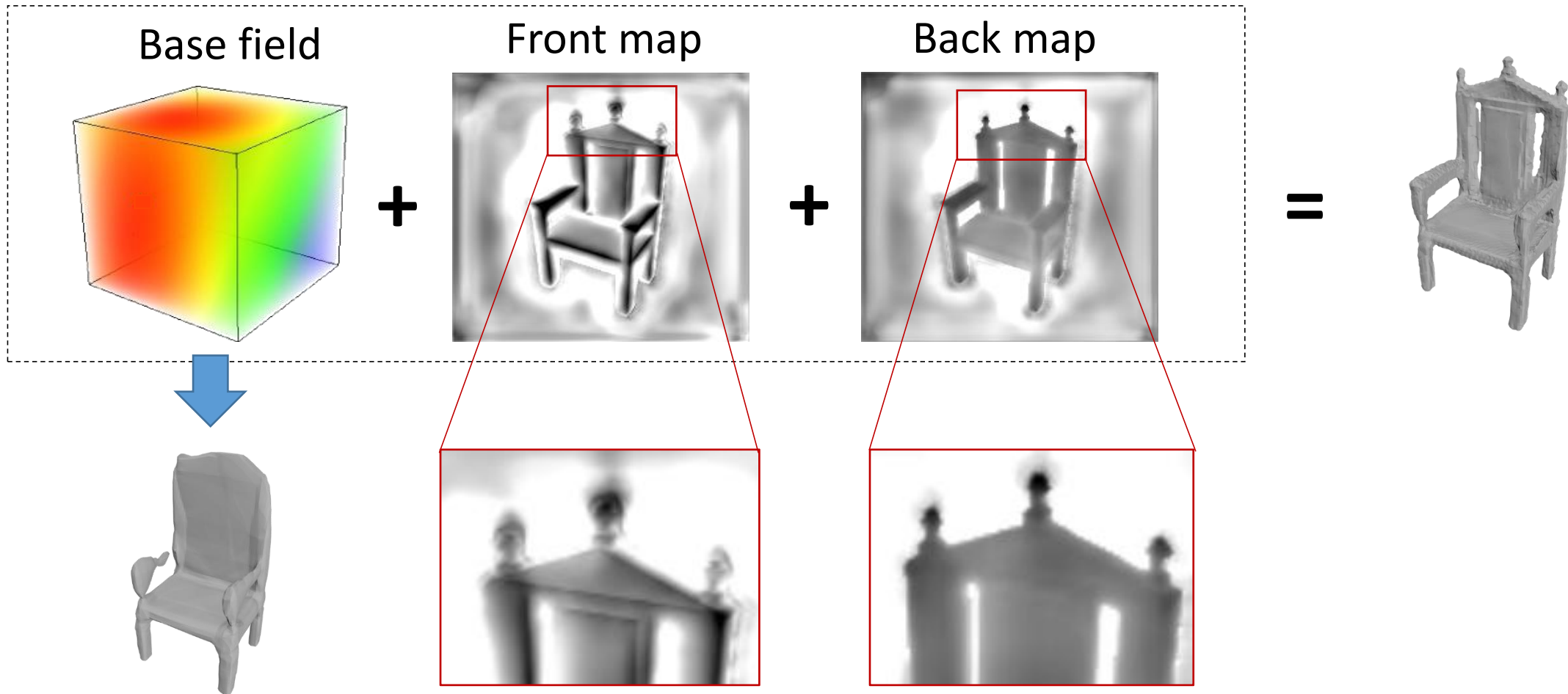
1. Detail Disentangled Implicit Field
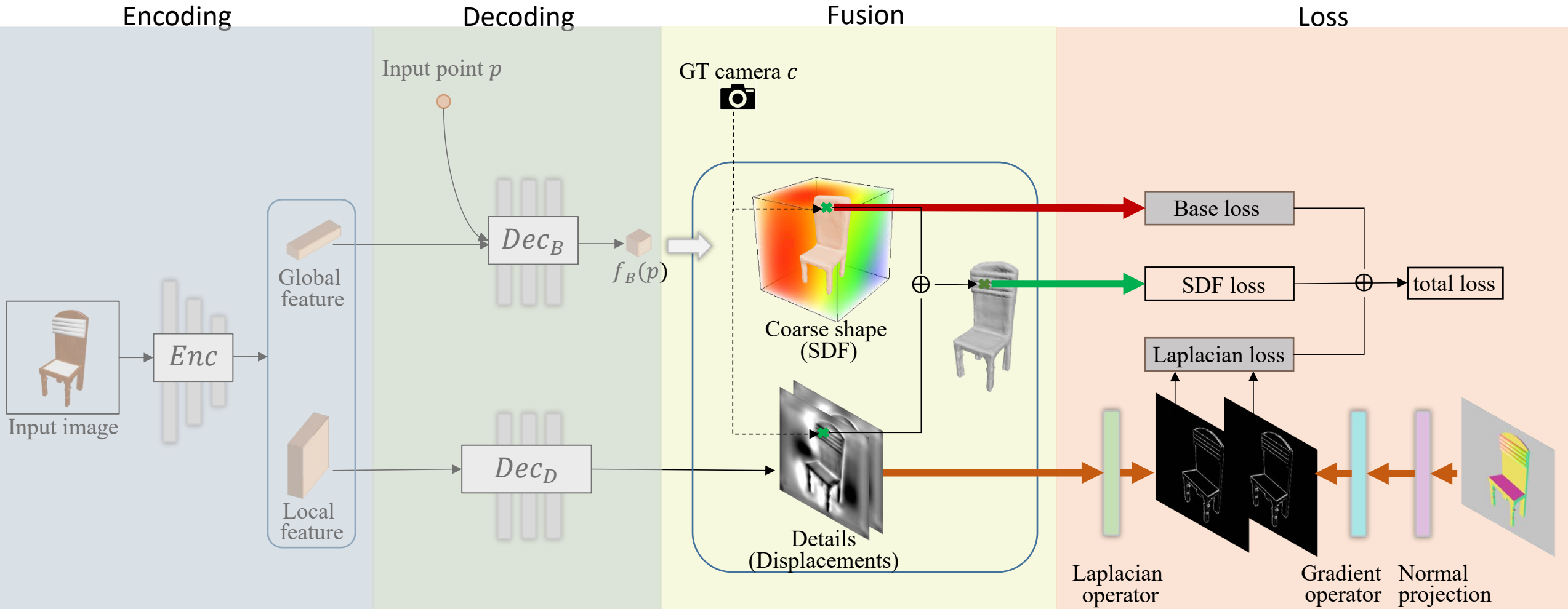
1. Detail Disentangled Implicit Field
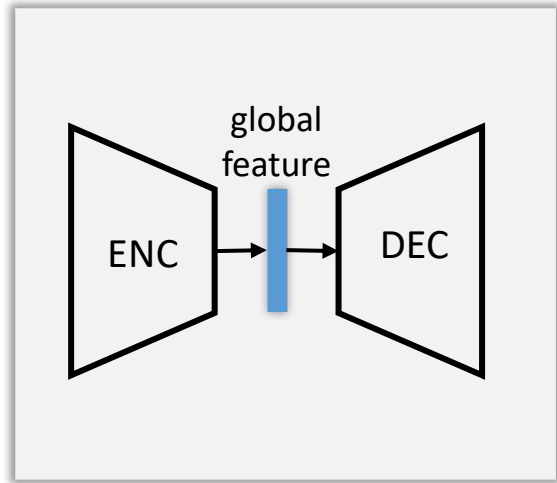
Single Decoder

Two-stream Decoder

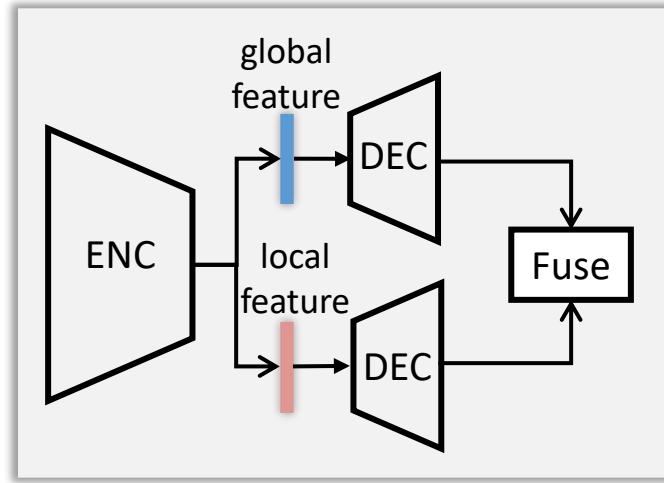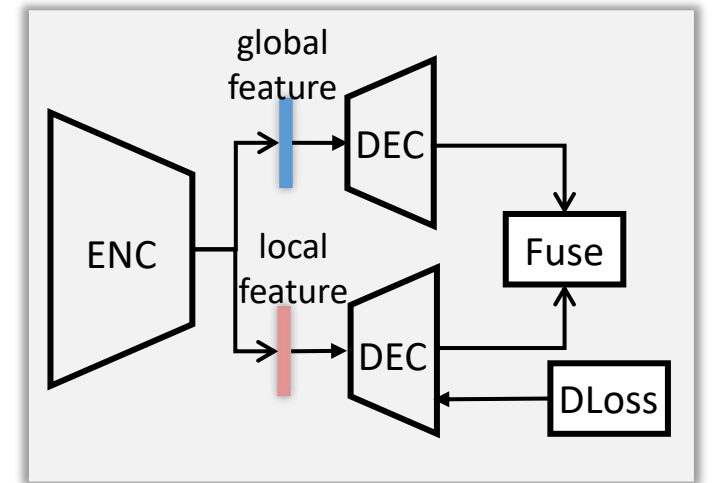Disentangled Representation

1. Detail Disentangled Implicit Field

Input IMNET DISN D²IM-Net GT
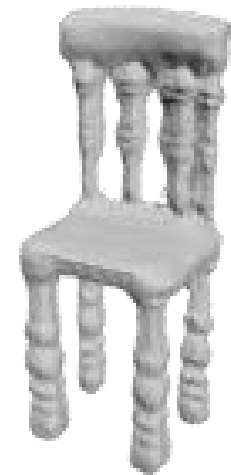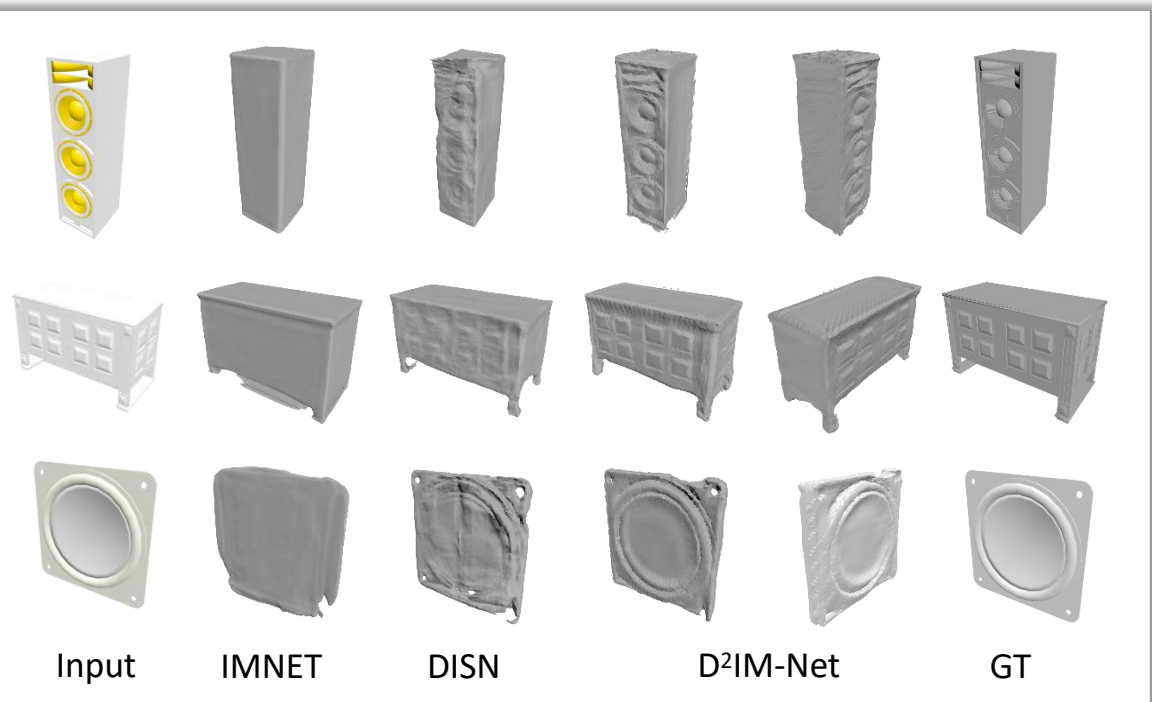
More accurate detail reconstruction

Detail transfer

The disentangled detail enables the transfer application.

Outline
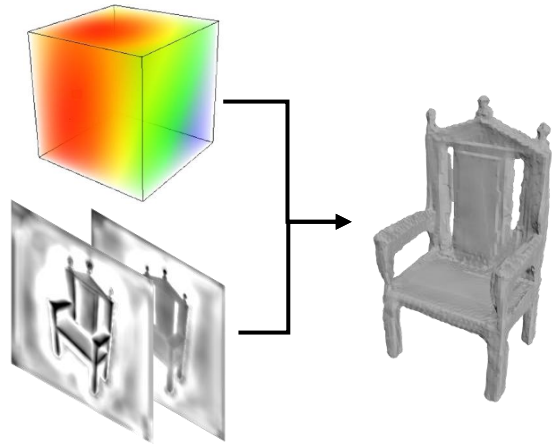
**Detail Disentangled
Implicit Field**

Pro: Better Geometric Detail
Reconstruction.

Key: <u>Laplacian loss</u> for the
unsupervised detail learning.

**Recursive
Implicit Field**

CAPRI

**Compact
CSG Representation**

Outline

**Detail Disentangled
Implicit Field**

Pro: Better Geometric Detail
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**Recursive
Implicit Field**

**Compact
CSG Representation**

CAPRI

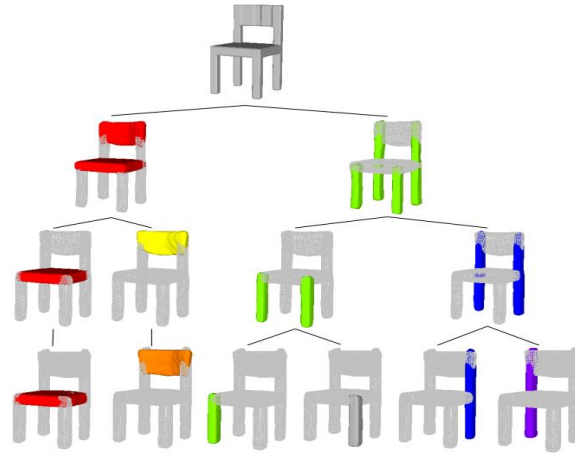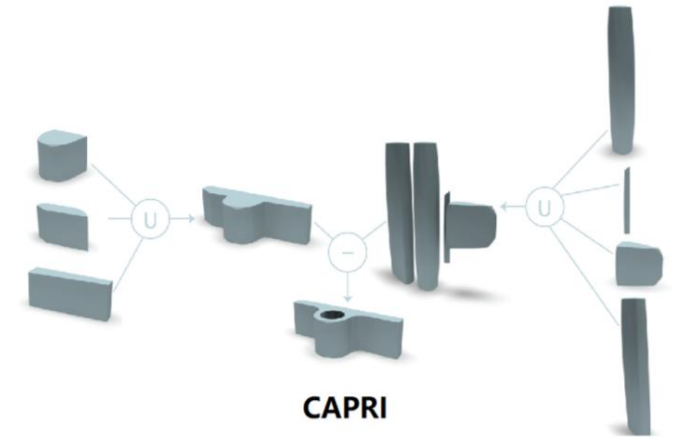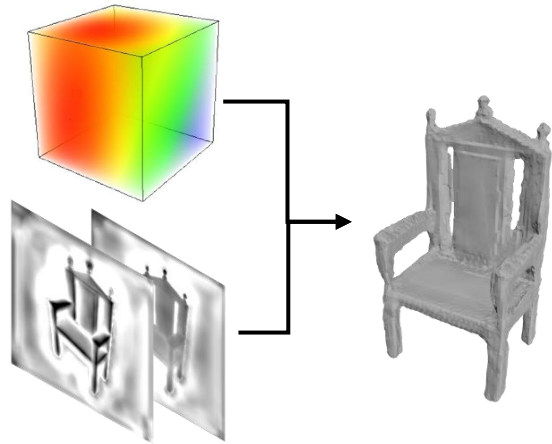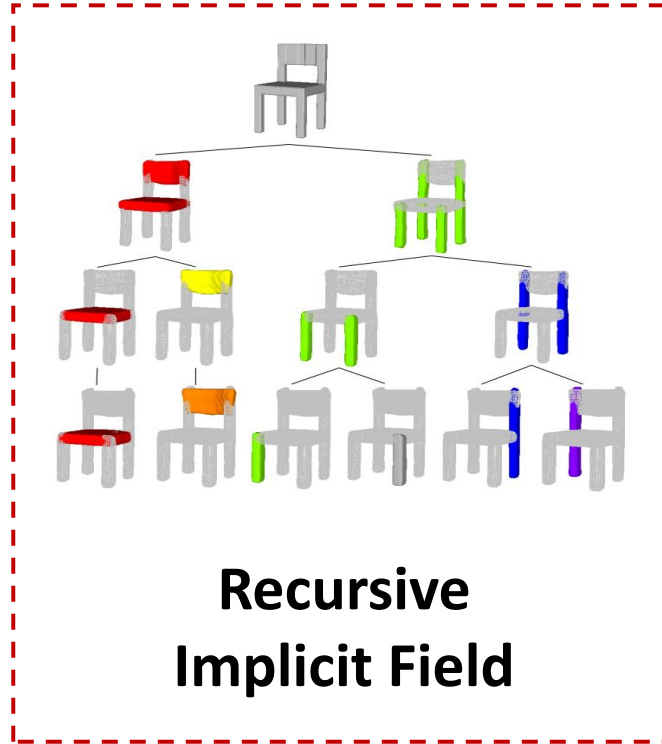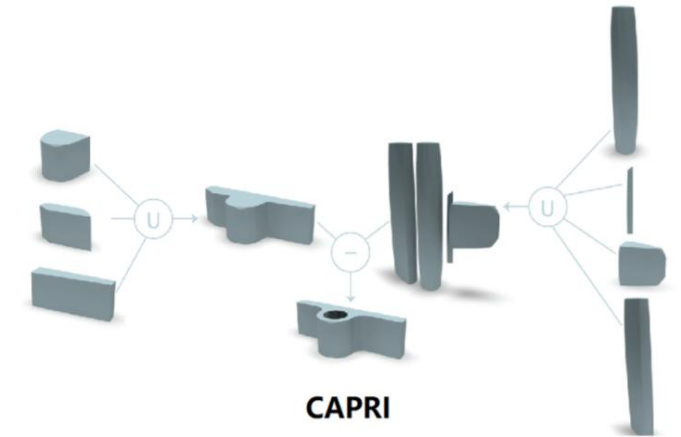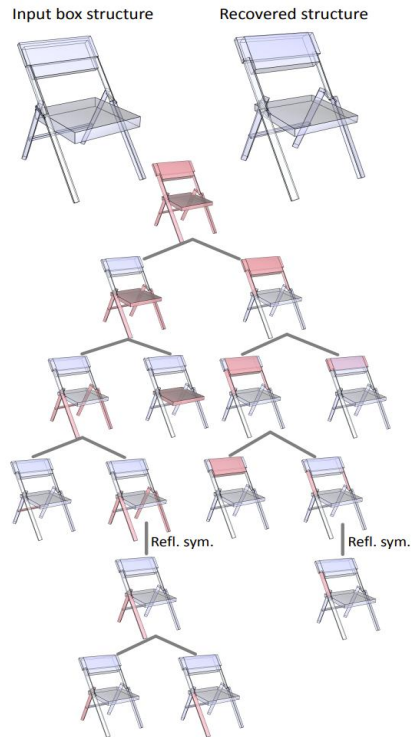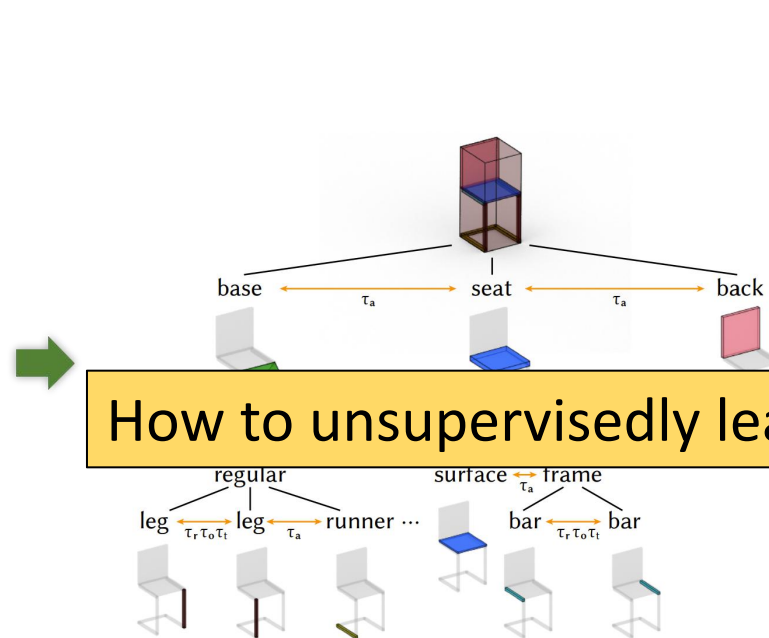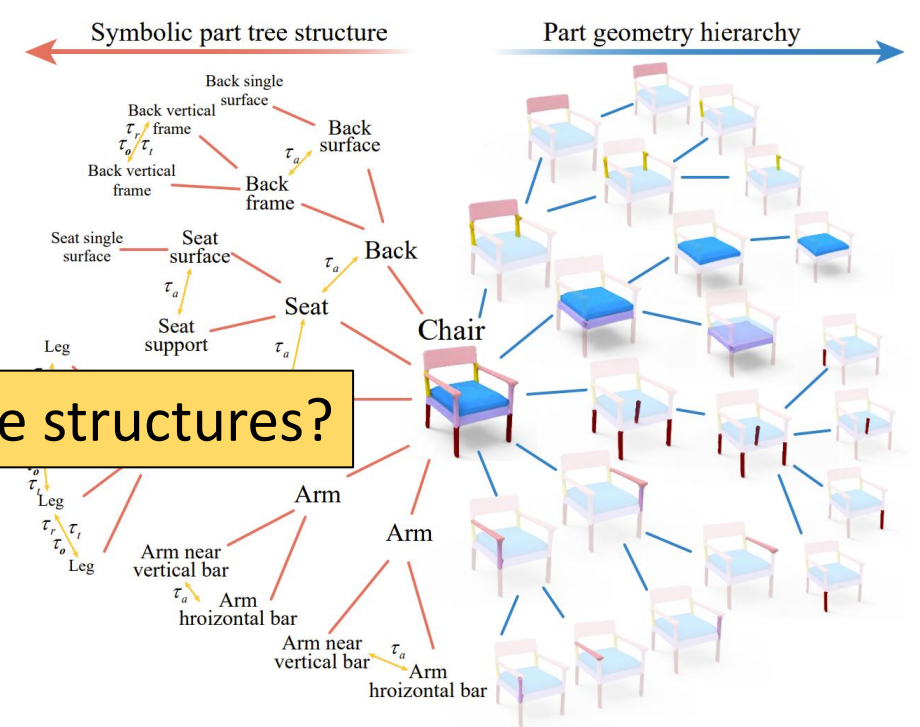# 2. Recursive Implicit Field

Input box structure   Recovered structure

Refl. sym.   Refl. sym.

[GRASS Siggraph 2017]

Binary Tree

base ⟷ τ_a ⟷ seat ⟷ τ_a ⟷ back

regular   surface ⟷ τ_a ⟷ frame

leg $\tau_r\tau_o\tau_t$ leg ⟷ τ_a ⟷ runner ⋯   bar $\tau_r\tau_o\tau_t$ bar

How to unsupervisedly learn the structures?

[StructureNet SIGA 2019]

N-ary Tree

Symbolic part tree structure   Part geometry hierarchy

Back single surface
Back vertical τ_r frame
τ_o / τ_t Back surface
Back vertical frame   Back frame   Back

Seat single surface   Seat surface   Seat
Seat support   Back

Leg

τ_t
Leg
τ_r / τ_t
τ_o
Leg   Arm near vertical bar   Arm
Arm hroizontal bar
Arm near vertical bar τ_a Arm hroizontal bar   Arm

Chair

[DSG-NET TOG 2022]

Disentangled
structure and geometry
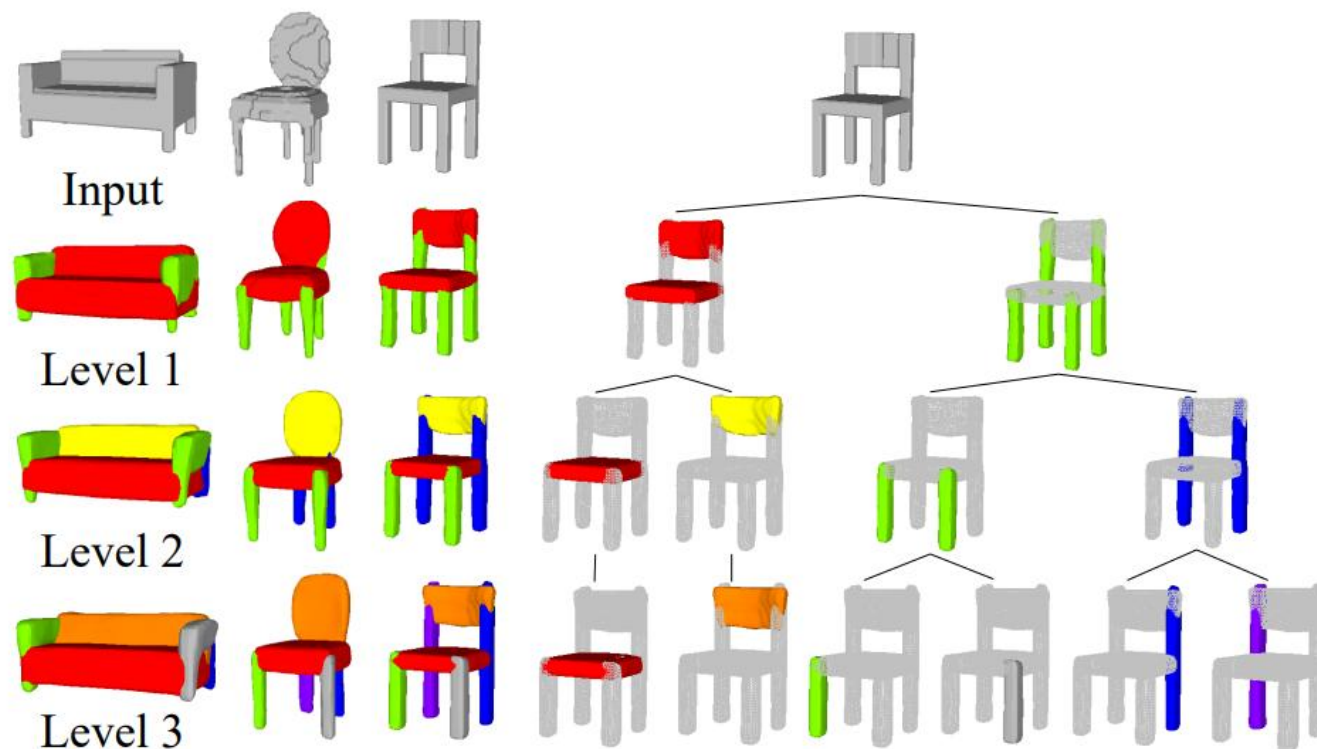
Input

Level 1

Level 2

Level 3

2. Recursive Implicit Field
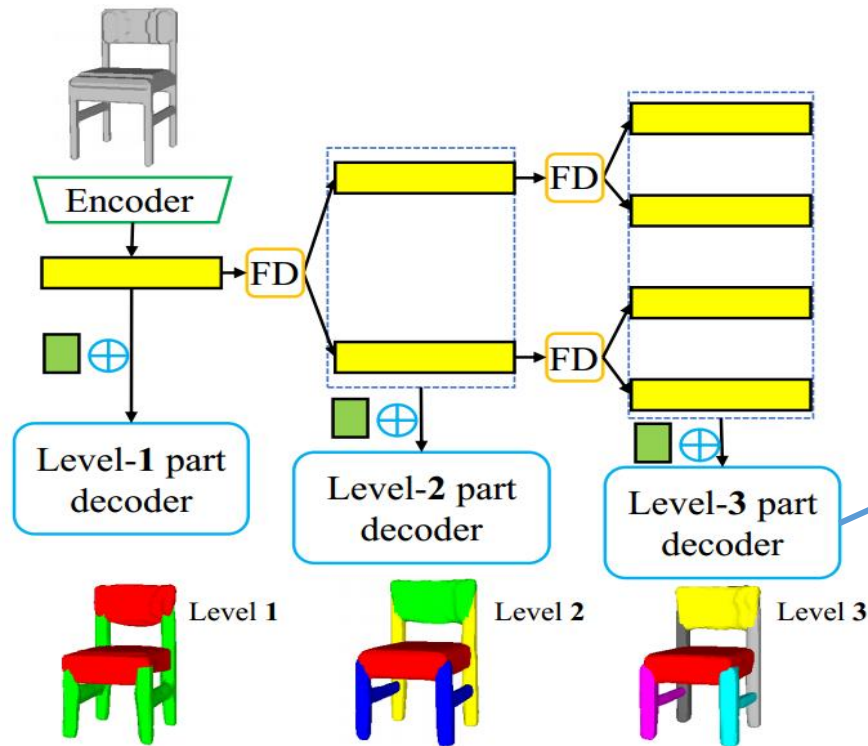
Branched reconstruction from implicit fields

1. Network bias with ReLU-based INR

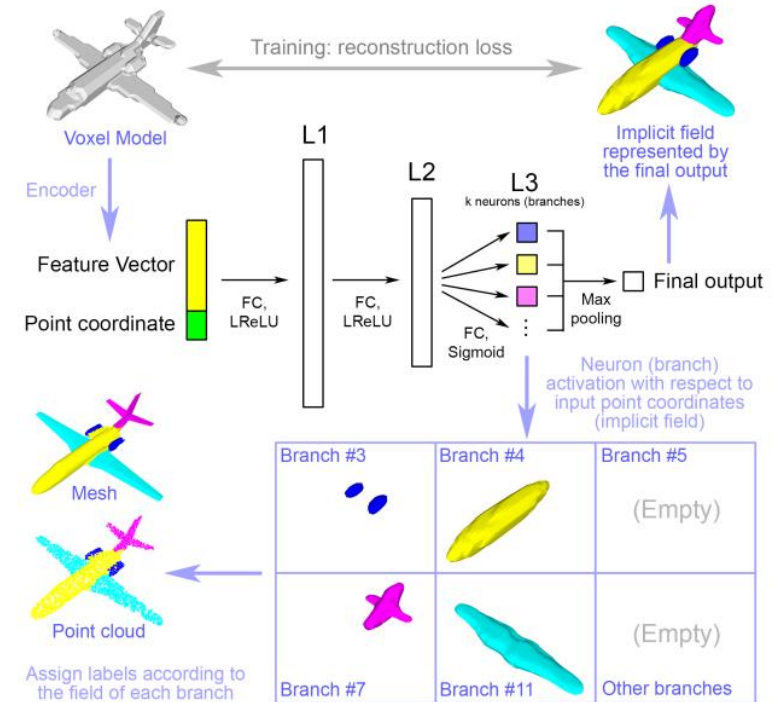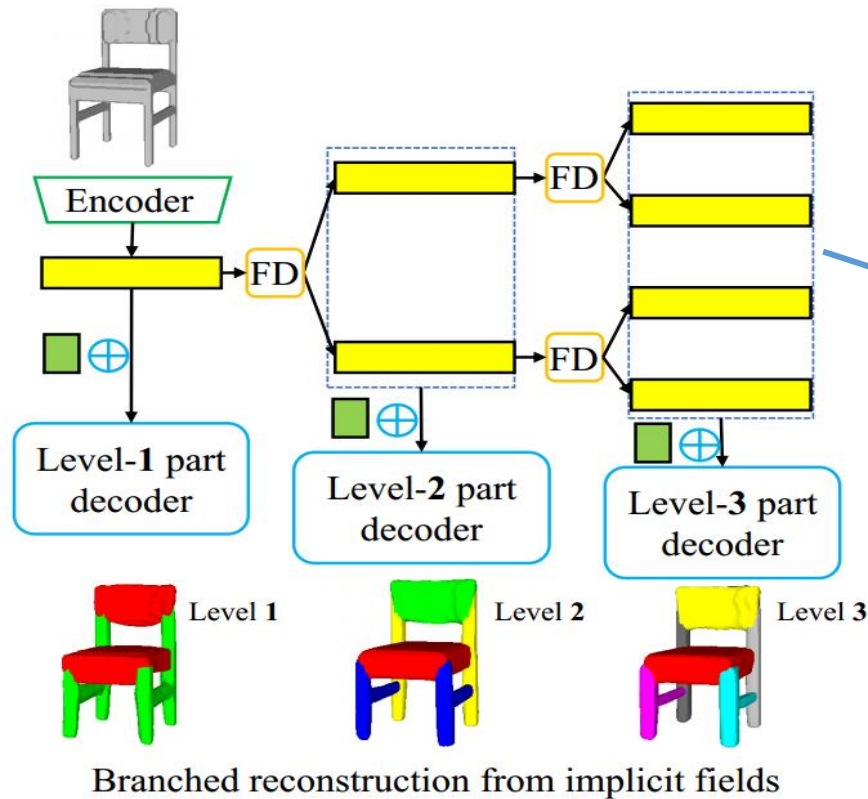[BAE-Net ICCV 2019]

2. Recursive Implicit Field

Branched reconstruction from implicit fields

1. Network bias with ReLU-based INR

2. Constraints from the loss functions
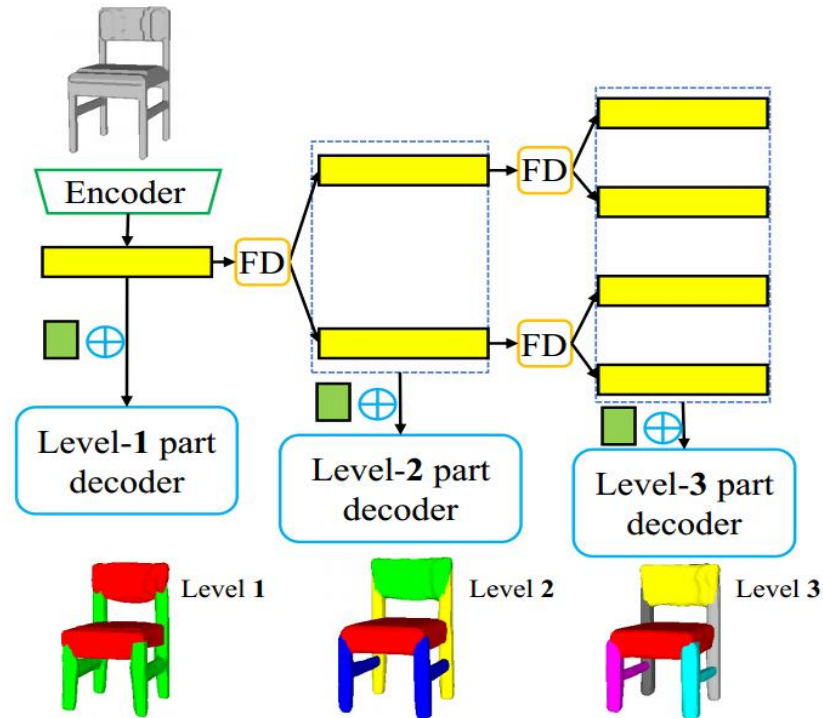
Reconstruction Loss:
- The union of each level should reconstruct the whole shape.

Decomposition Loss：
- Each parent is the union of its two child parts.

Recursive training strategy

2. Recursive Implicit Field

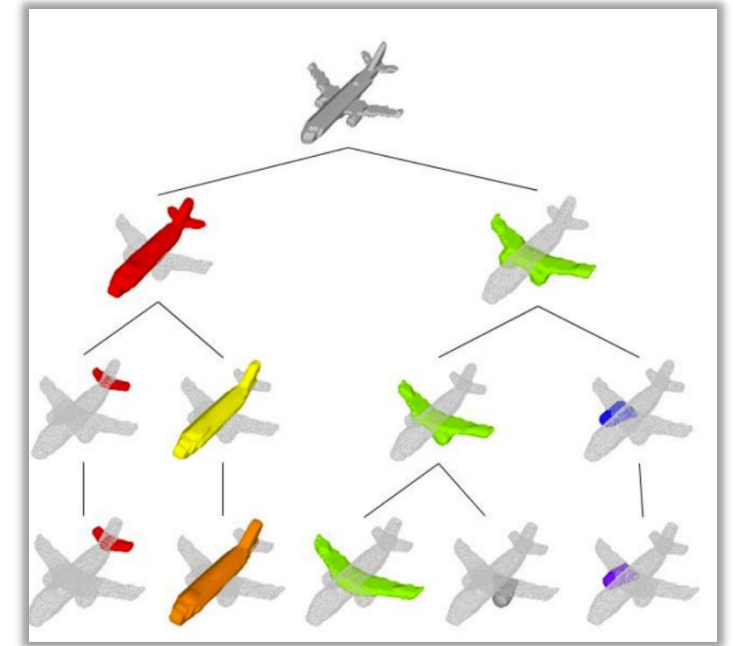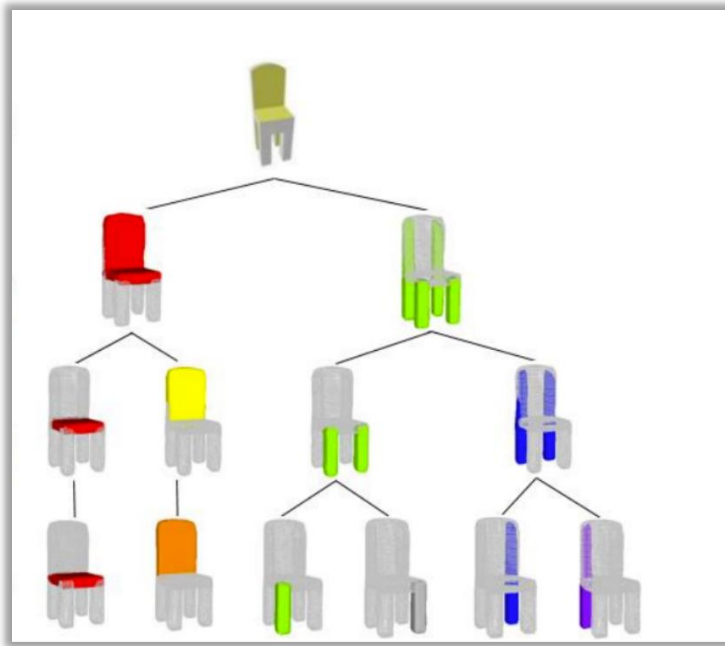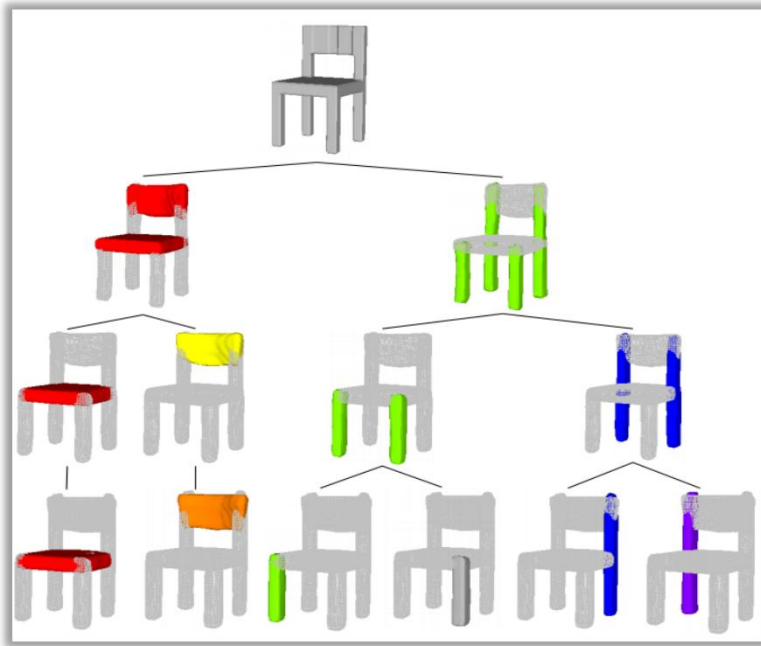Branched reconstruction from implicit fields

[RIM-Net CVPR 2022]

1. Network bias with ReLU-based INR

2. Constraints from the loss functions
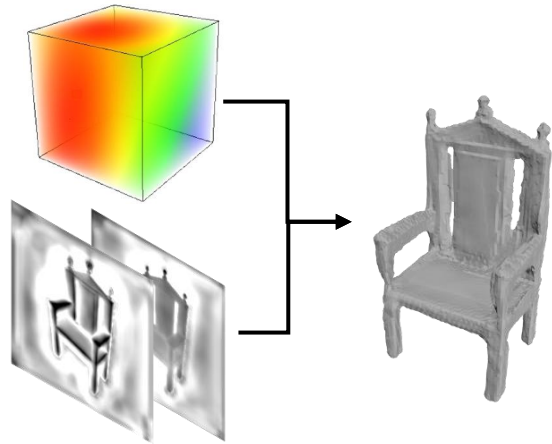
3. Per-point gaussian parameters

2. From objects to parts

We obtain:

- Hierarchical implicit fields to represent the shape structure
- Consistent segmentation
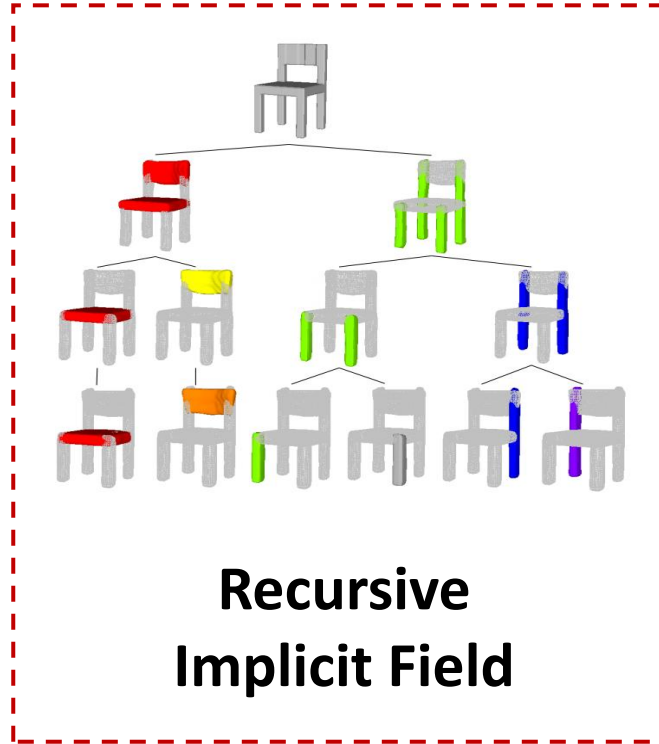- Better reconstruction accuracy

Outline

**Detail Disentangled
Implicit Field**
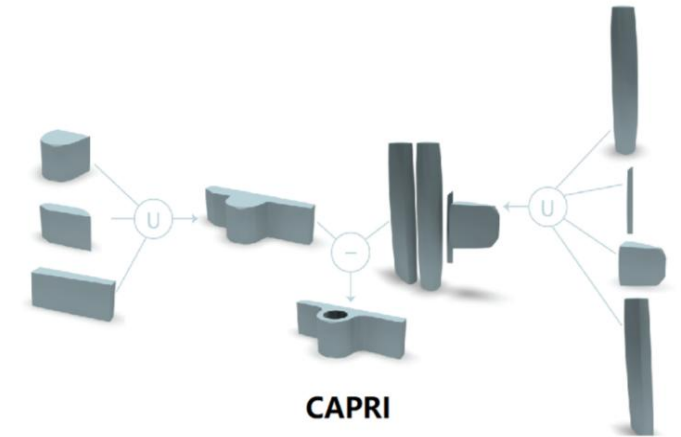
Pro: Better geometric detail
Reconstruction.

Key: Laplacian loss for the
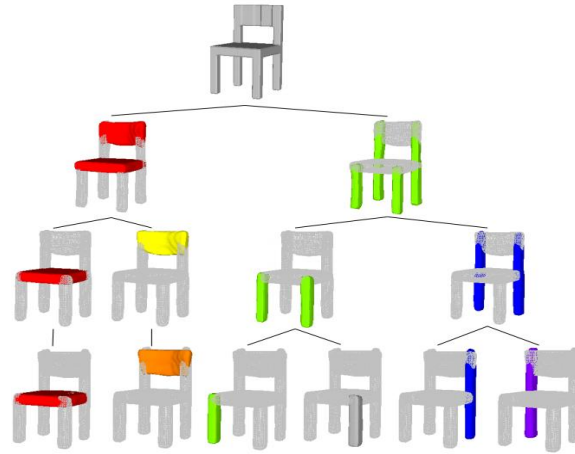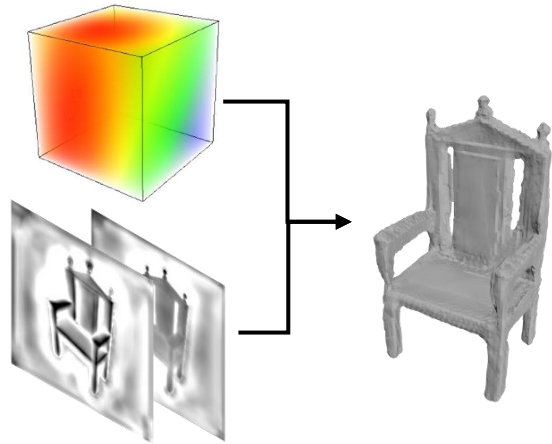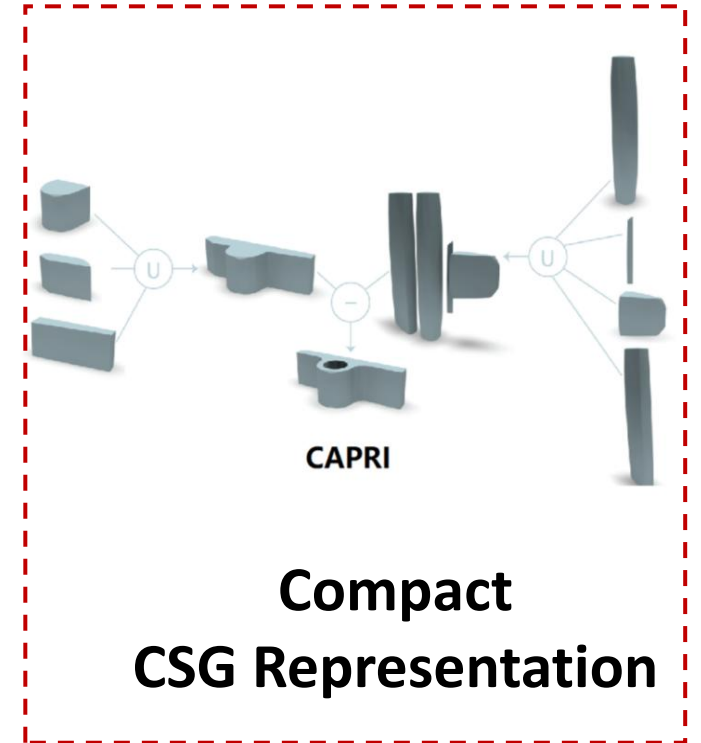unsupervised detail learning.

**Recursive
Implicit Field**

Pro: Consistent hierarchical
object structure

Key: Network bias and loss
for the unsupervised learning.

**Compact
CSG Representation**

CAPRI

Outline

**Detail Disentangled
Implicit Field**

Pro: Better geometric detail
Reconstruction.

Key: Laplacian loss for the
unsupervised detail learning.

**Recursive
Implicit Field**

Pro: Consistent hierarchical
object structure

Key: Network bias and loss
for the unsupervised learning.

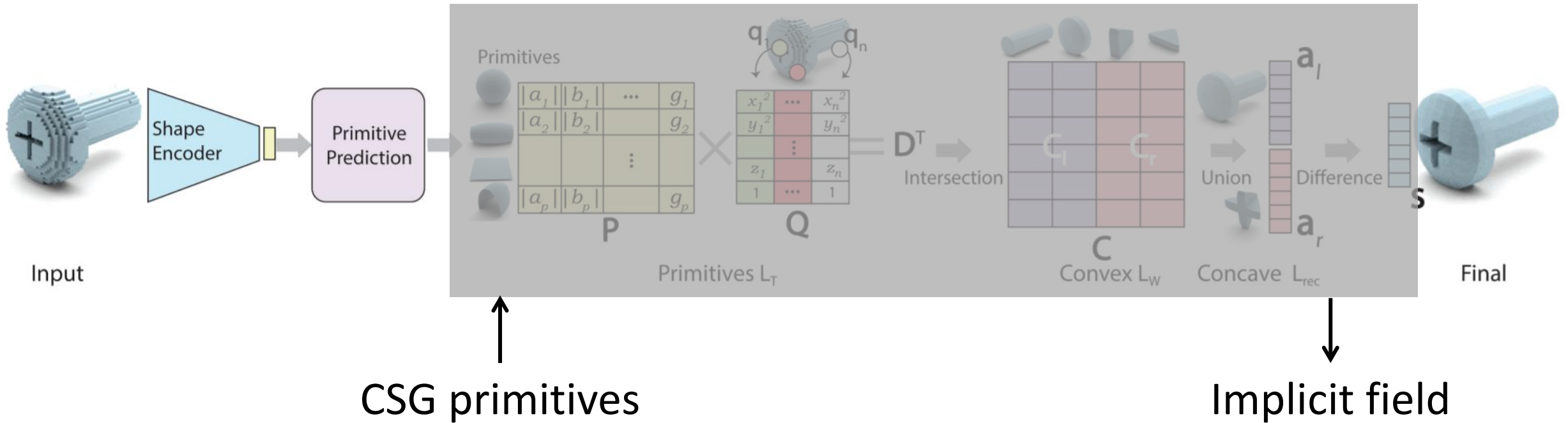CAPRI

**Compact
CSG Representation**

3. Compact CSG Representation
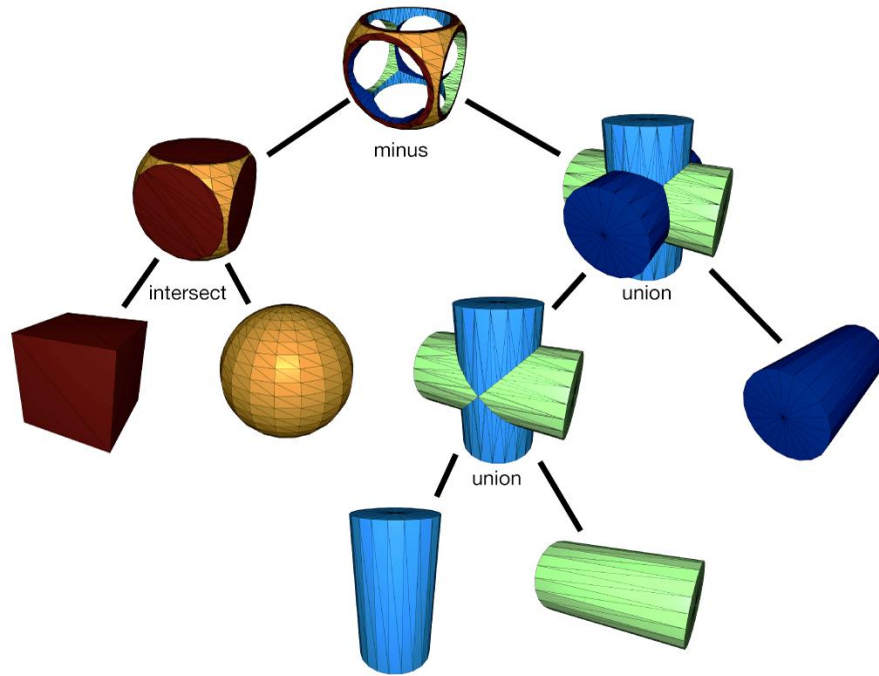
CSG Representation
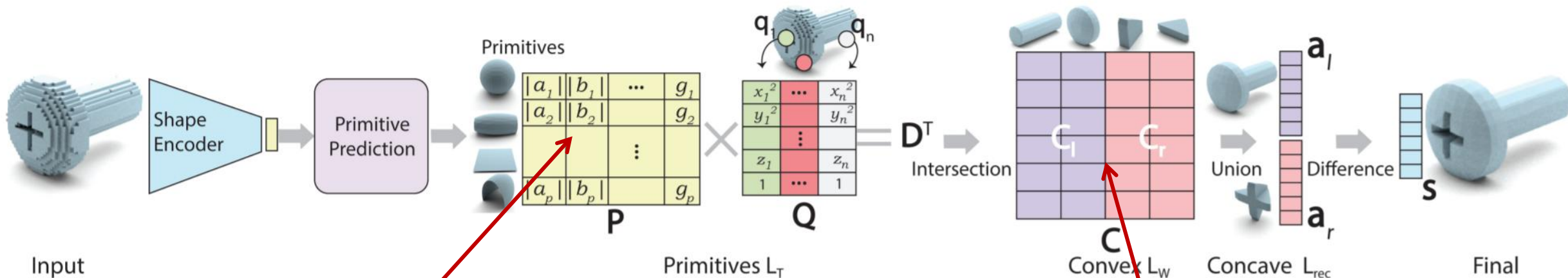
How to unsupervisedly learn the CSG commands?

3. Compact CSG Representation

CSG primitives

Implicit field

3. Compact CSG Representation

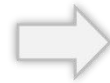Primitive parameter prediction.

$$ax^2 + by^2 + cz^2 + dx + ey + fz + g = 0.$$

Assembly prediction.

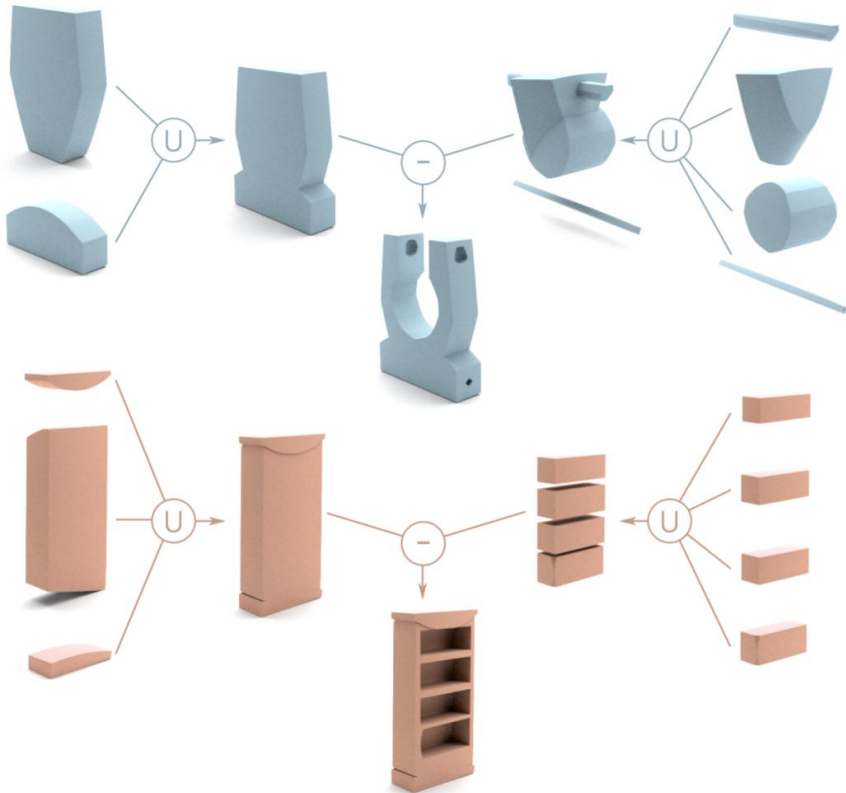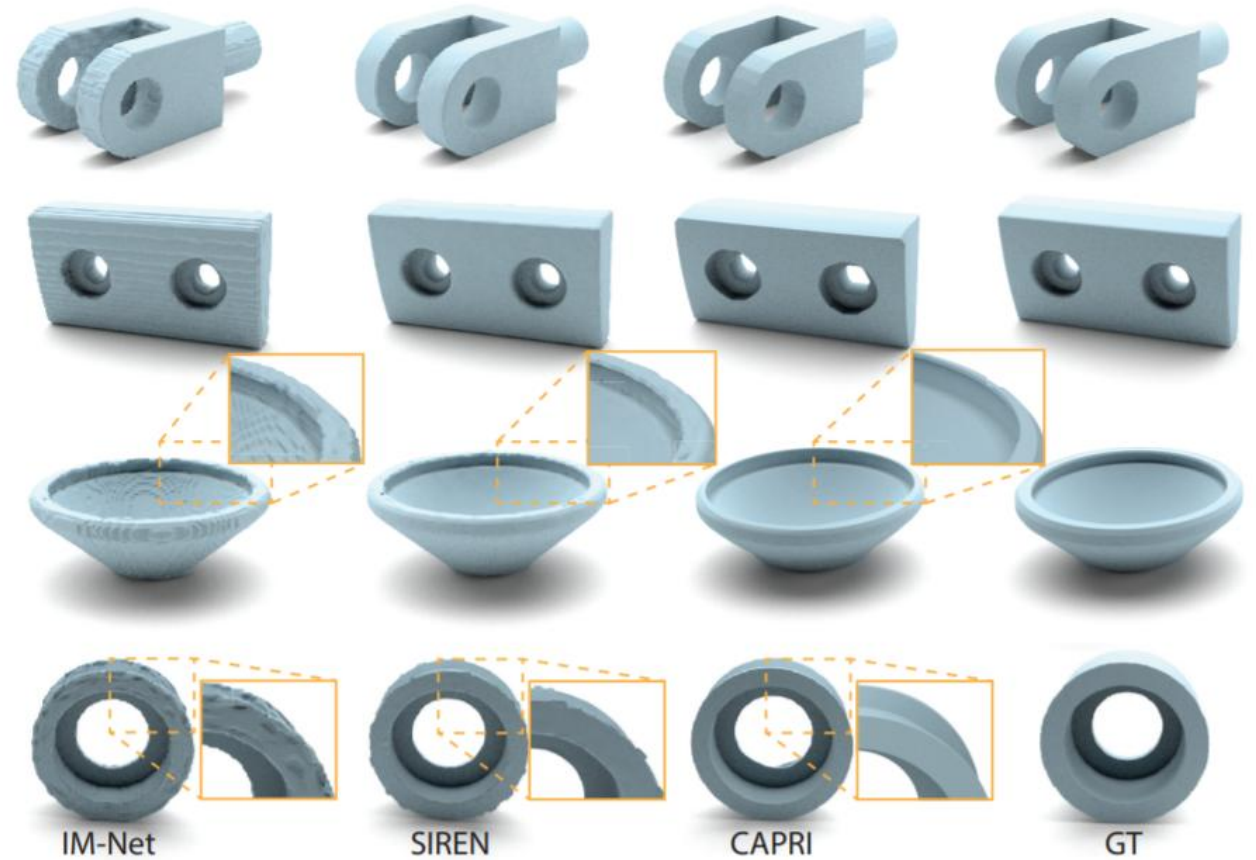|			
Intersection	$\mathbf{C} = \text{relu}(\mathbf{D})\mathbf{T}$	$\begin{cases} 0 & \text{inside,} \\ > 0 & \text{outside.} \end{cases}$	
Union	$\mathbf{a}_l^*(j) = \min_{i < \frac{c}{2}}(\mathbf{C}_l(j, i))$	$\begin{cases} 0 & \text{inside,} \\ > 0 & \text{outside,} \end{cases}$	
Difference	$\mathbf{s}^*(j) = \max(\mathbf{a}_l^*(j), \alpha - \mathbf{a}_r^*(j))$	$\begin{cases} 0 & \text{inside,} \\ > 0 & \text{outside,} \end{cases}$	

3. Compact CSG Representation
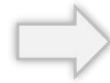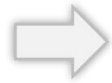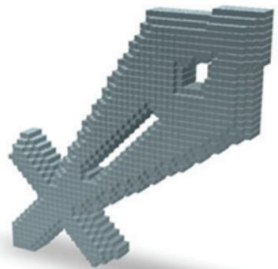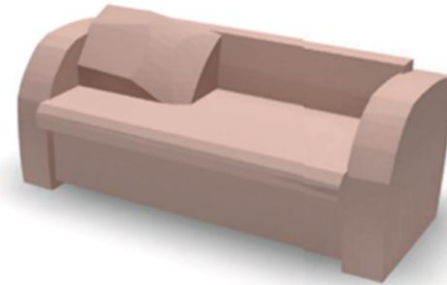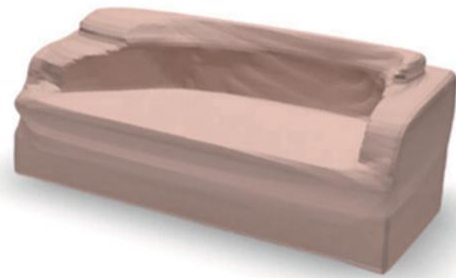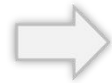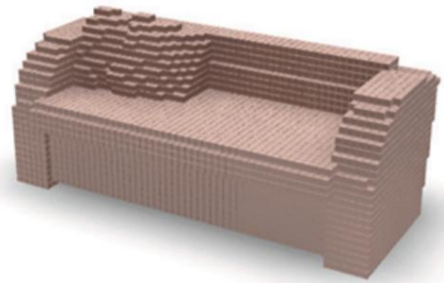
Input   CAPRI w.o FT   CAPRI   GT
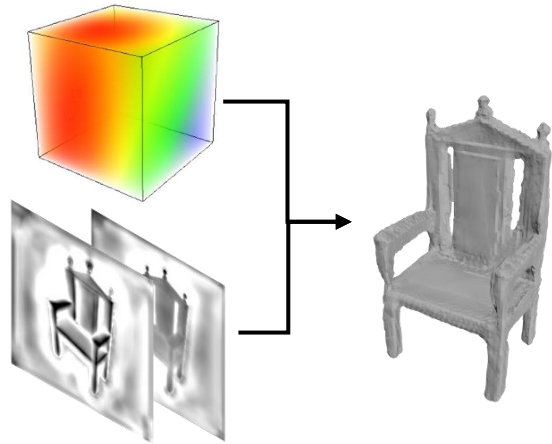
3. Compact CSG Representation

Compact CSG structure
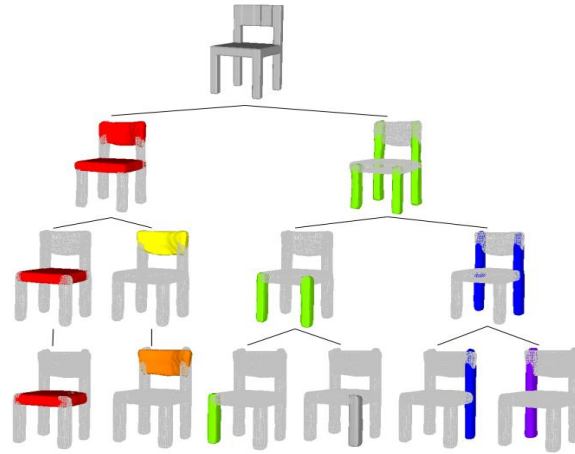
Better sharp feature

IM-Net   SIREN   CAPRI   GT

Outline

**Detail Disentangled
Implicit Field**

**Recursive
Implicit Field**

**Compact
CSG Representation**

Pro: Better geometric detail
Reconstruction.

Pro: Consistent hierarchical
object structure

Pro: Compact structure and
better sharp features

Key: Laplacian loss for the
unsupervised detail learning.

Key: Network bias and loss
for the unsupervised learning.

Key: Differentiable transform
for the unsupervised learning.

Thank you!