

# Rectified Point Flow: Generic Point Cloud Pose Estimation

*NeurIPS 2025 (Spotlight)*

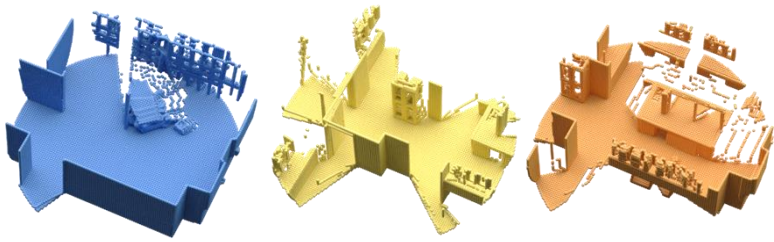
Tao Sun\*, Liyuan Zhu\*, Shengyu Huang,  
Shuran Song, Iro Armeni



# Why Pose Estimation?

Many 3D vision tasks can be reduced to part-level pose estimation.

Point Cloud Registration



Fragments Reassembly



Figures from GARF



Robotic Assembly

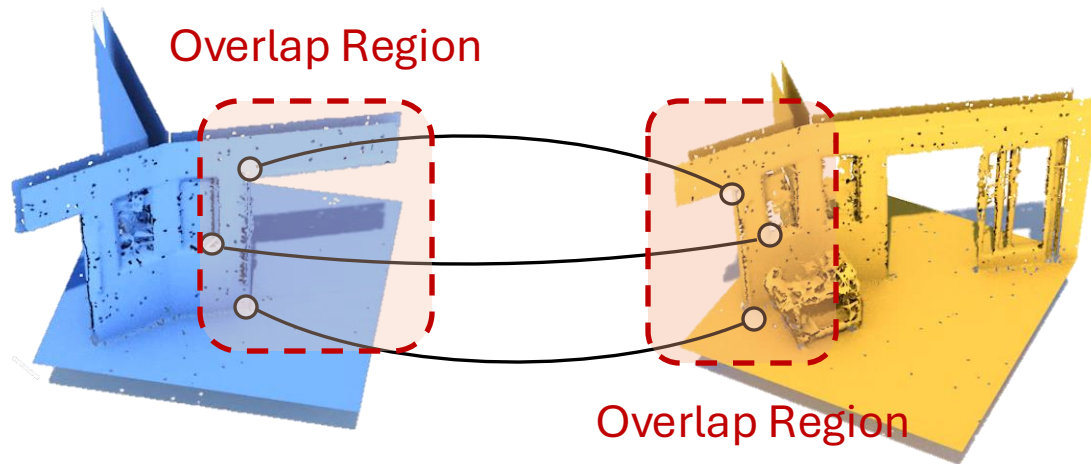


# Why Pose Estimation Can Be **Hard**?

1. Most registration methods rely on correspondence pairs.

Enough Overlap

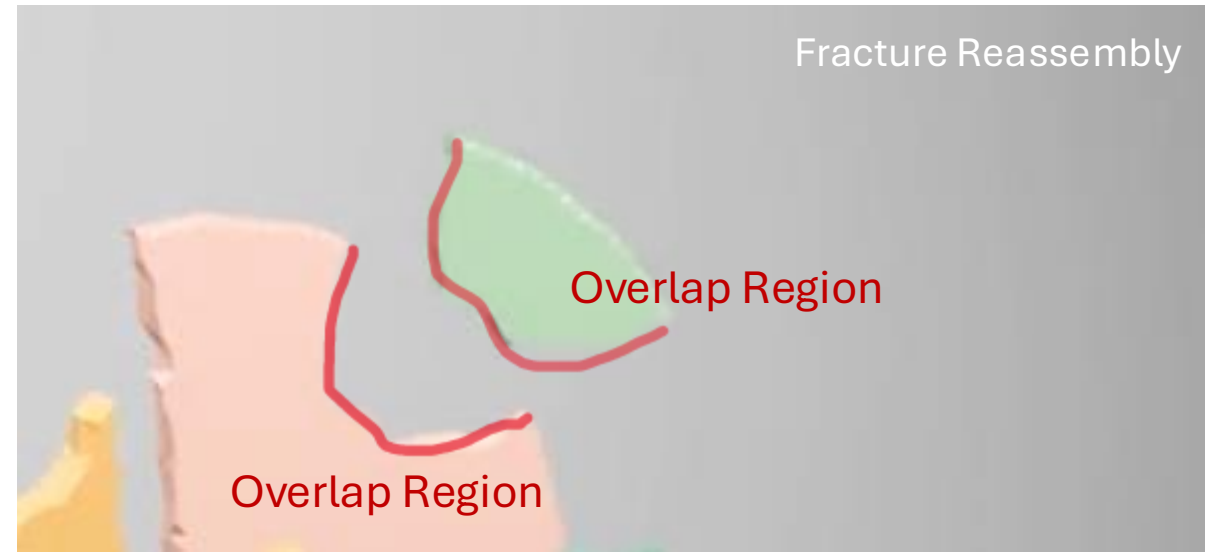
Room Scan Registration



Overlap Ratio > 10%

Not Enough Overlap

Fracture Reassembly



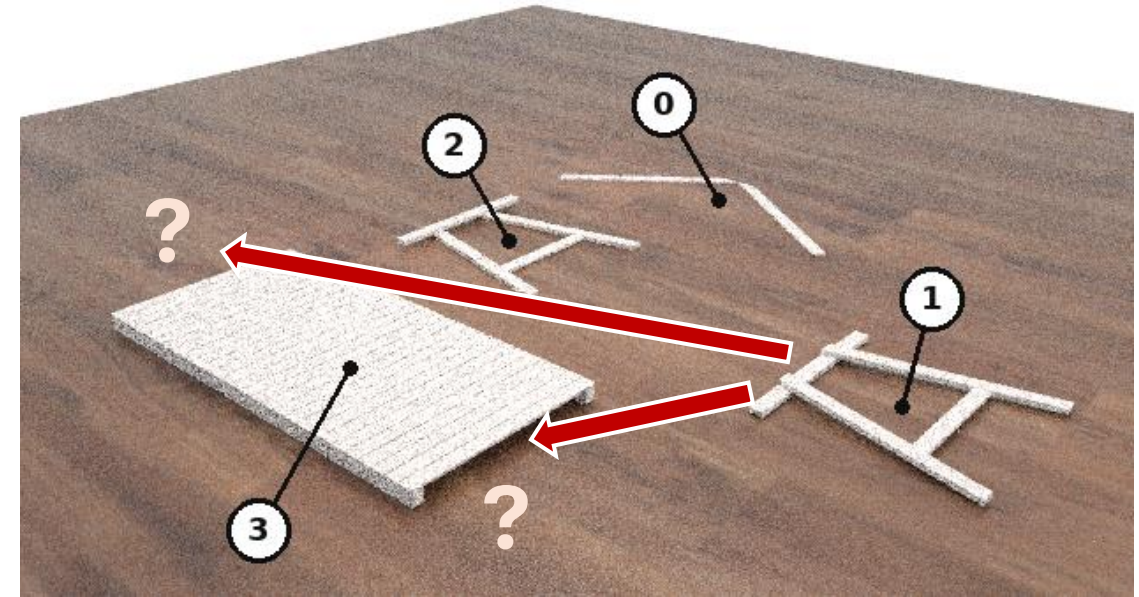
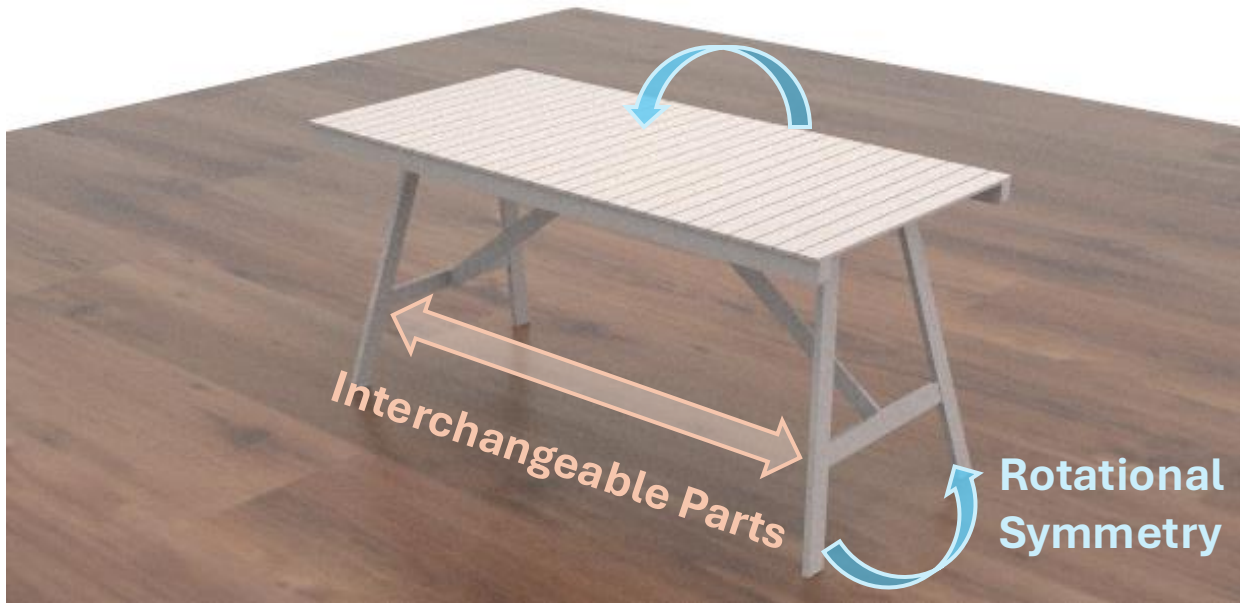
Overlap Ratio < 1%

We need a formulation **does not rely on** point or feature correspondences.



# Why Pose Estimation Can Be **Hard**?

2. Part-level symmetry further complicates the issue.



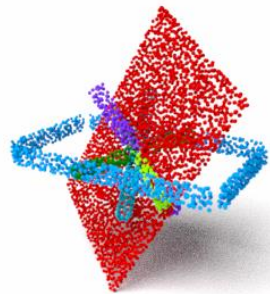
Multiple Plausible Configurations Exists

Pose estimation is fundamentally a **generative problem**.

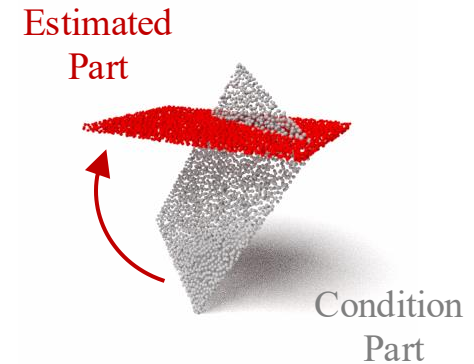
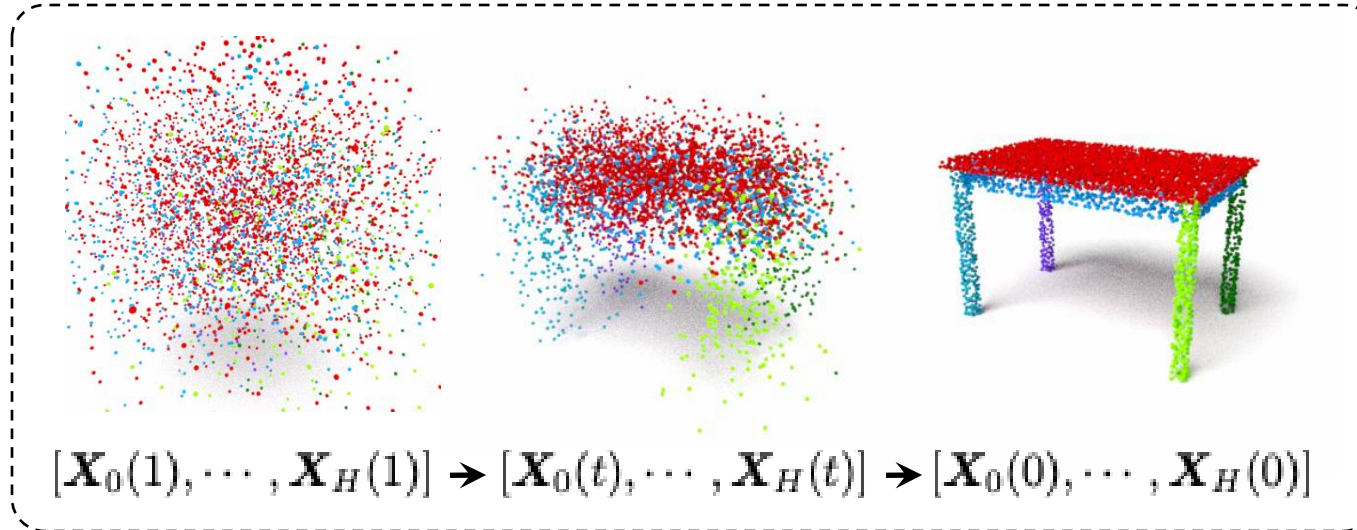
# Our Solution: Pose from Shape

First shape, then pose.

A Euclidean-space Flow



Condition  
Point Clouds

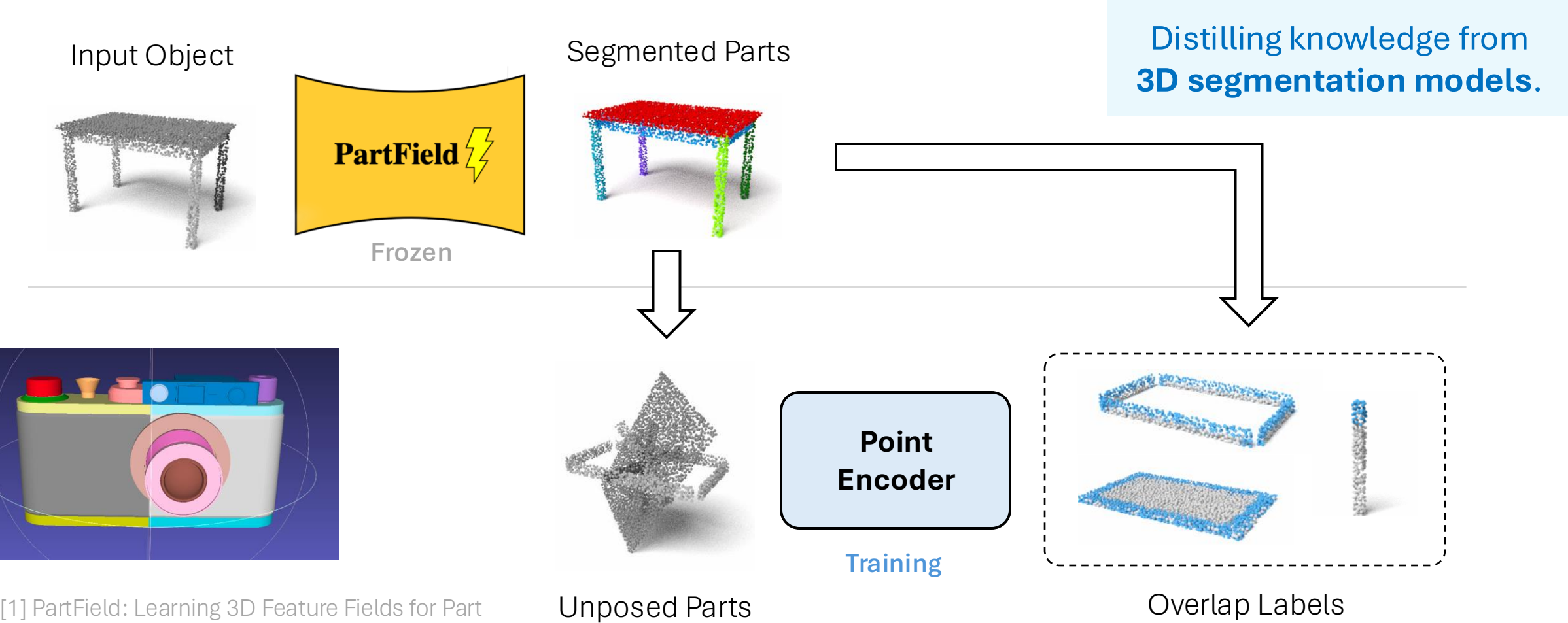


Pose Estimation  
by SVD

Shape is independent of **correspondence** and encodes all the **symmetry** information.

# Overlap-aware Pretraining

Large-scale pretraining with additionally Objaverse data via PartField [1] distillation



[1] PartField: Learning 3D Feature Fields for Part Segmentation and Beyond [ICCV 2025]



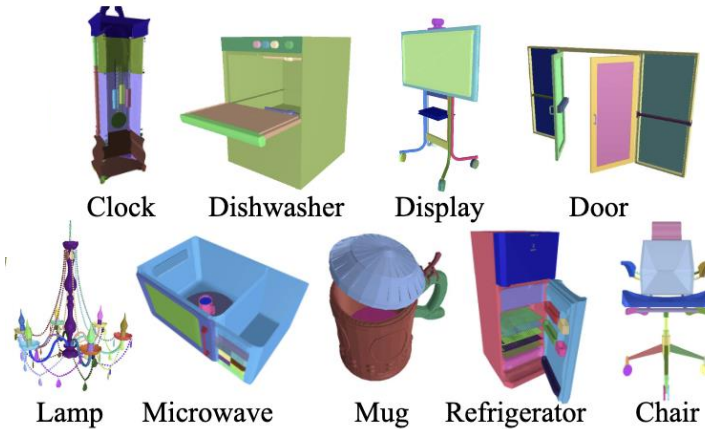
# Scalable to Diverse Tasks and Datasets

Task:

Assembly

Registration

PartNet



IKEA-Manual



BreakingBad



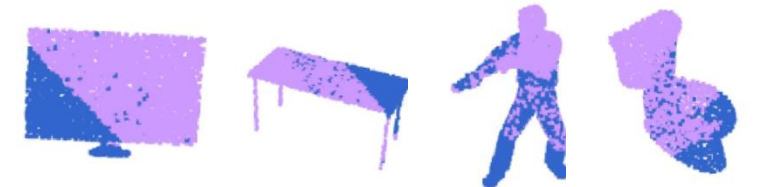
TwoByTwo



TUD-L



ModelNet-40



# Scalable to Diverse Part Definition

Task: Assembly Registration

## PartNet



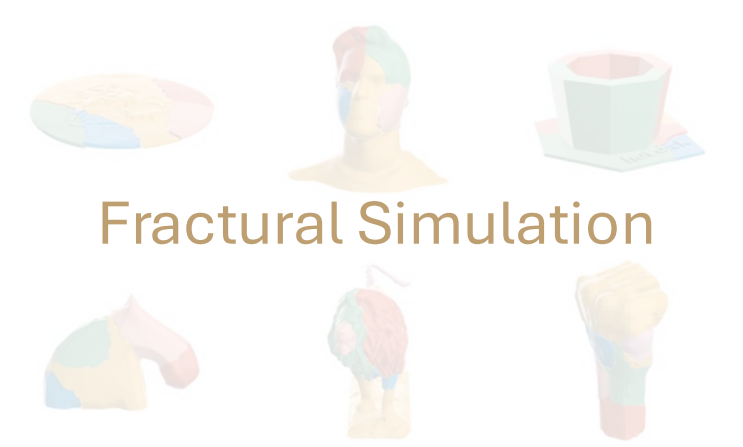
Semantics and Function

## IKEA-Manual



Reusability and Packing Efficiency

## BreakingBad



Fractural Simulation

## TwoByTwo



Insertable Parts

## TUD-L



Real RGBD Scan

## ModelNet-40



Random Plane Cropping



# Flow Trajectories

Assembly prediction given unposed parts

Input (condition)



Generation

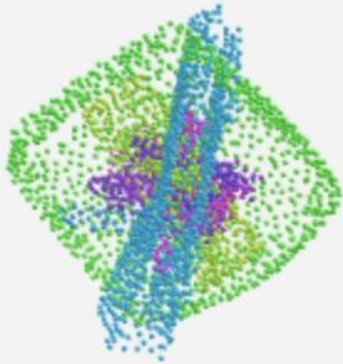


# Flow Trajectories

Assembly prediction given unposed parts

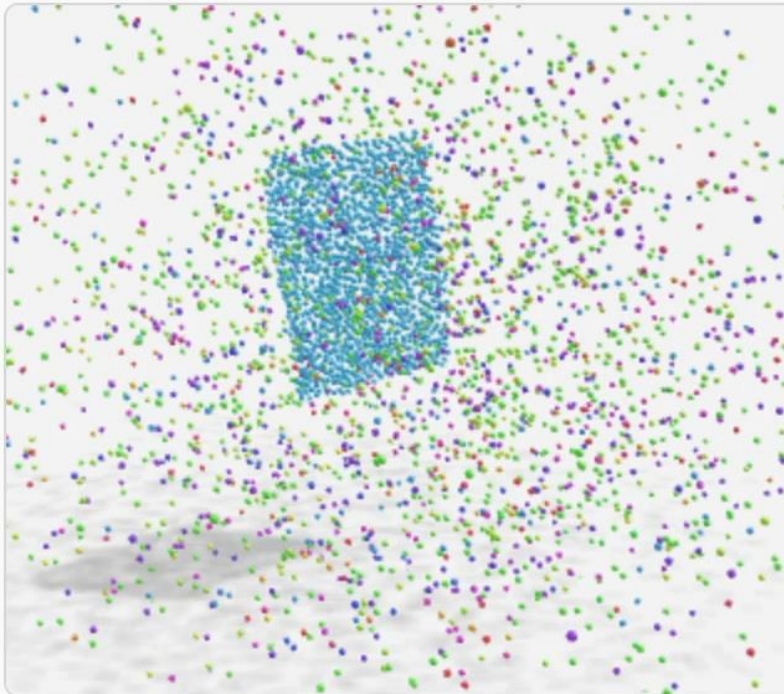
## Condition

Unposed Part Point Clouds



## Generation

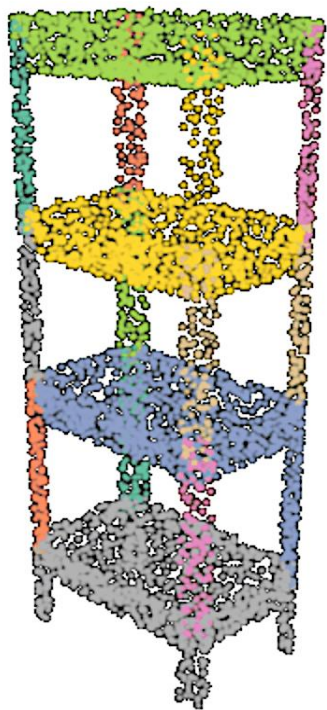
Possible Assembled Point Clouds



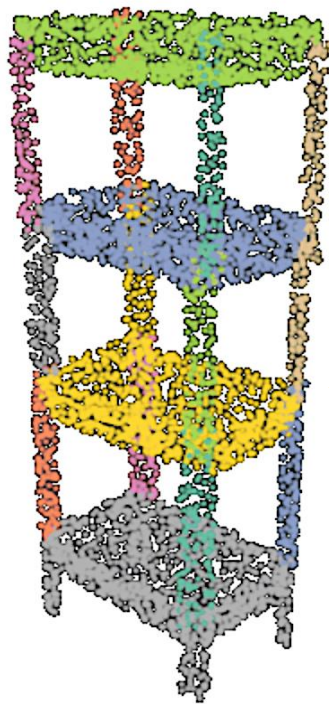


# Learning Part Symmetry by Construction

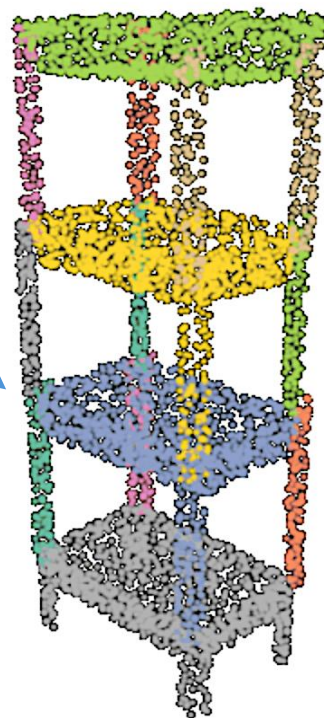
Without any symmetry labels



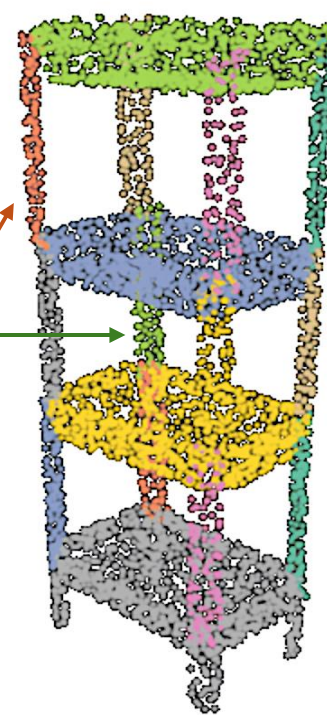
Ground Truth



Generated  
Result 1



Generated  
Result 2



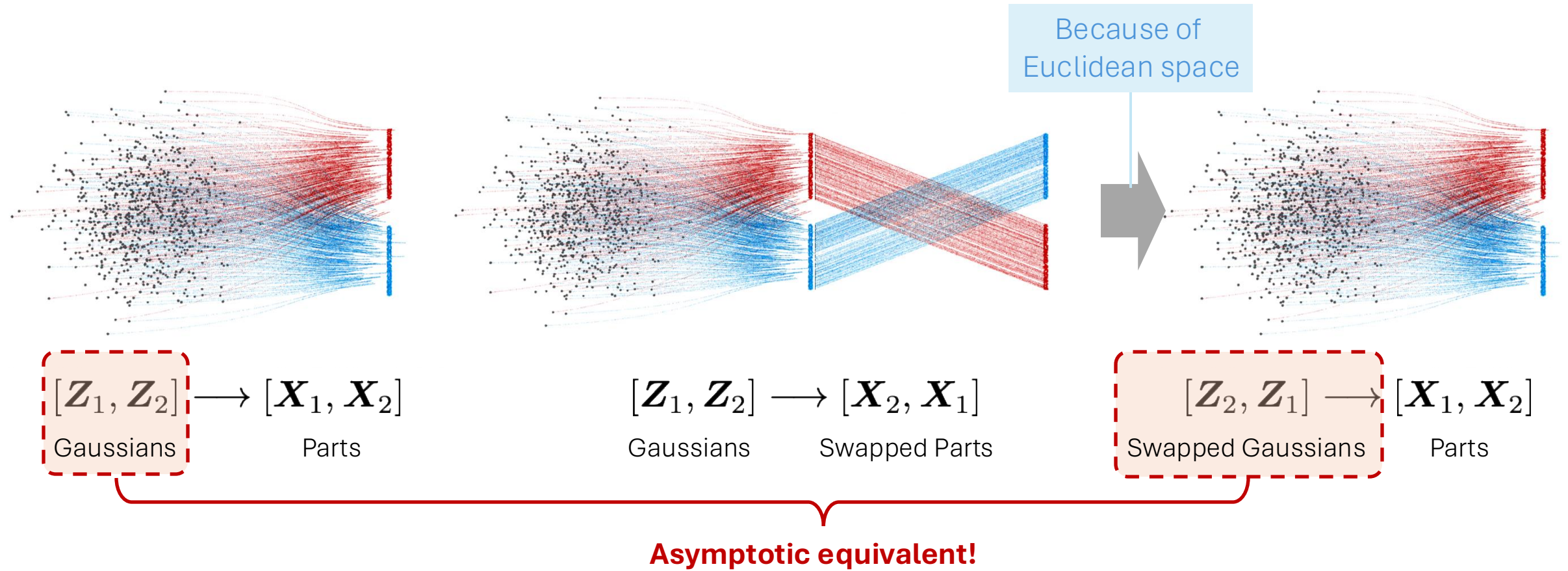
Generated  
Result 3

**Model swaps  
2 middle baskets  
and 12 vertical bars.**



# Learning Part Symmetry by Construction

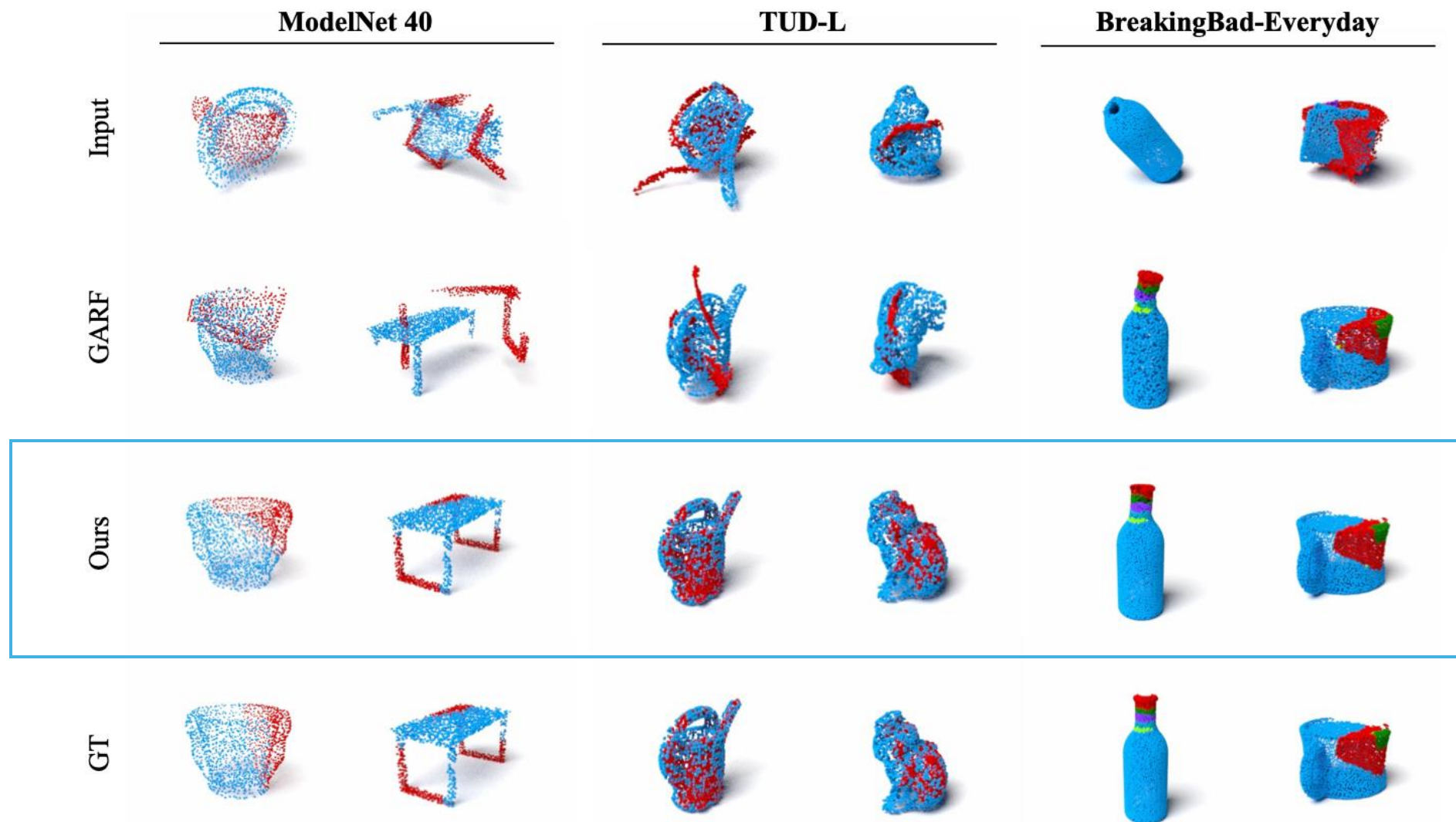
For part interchangeability and arbitrary part segmentation



# Experiments: Shape Assembly

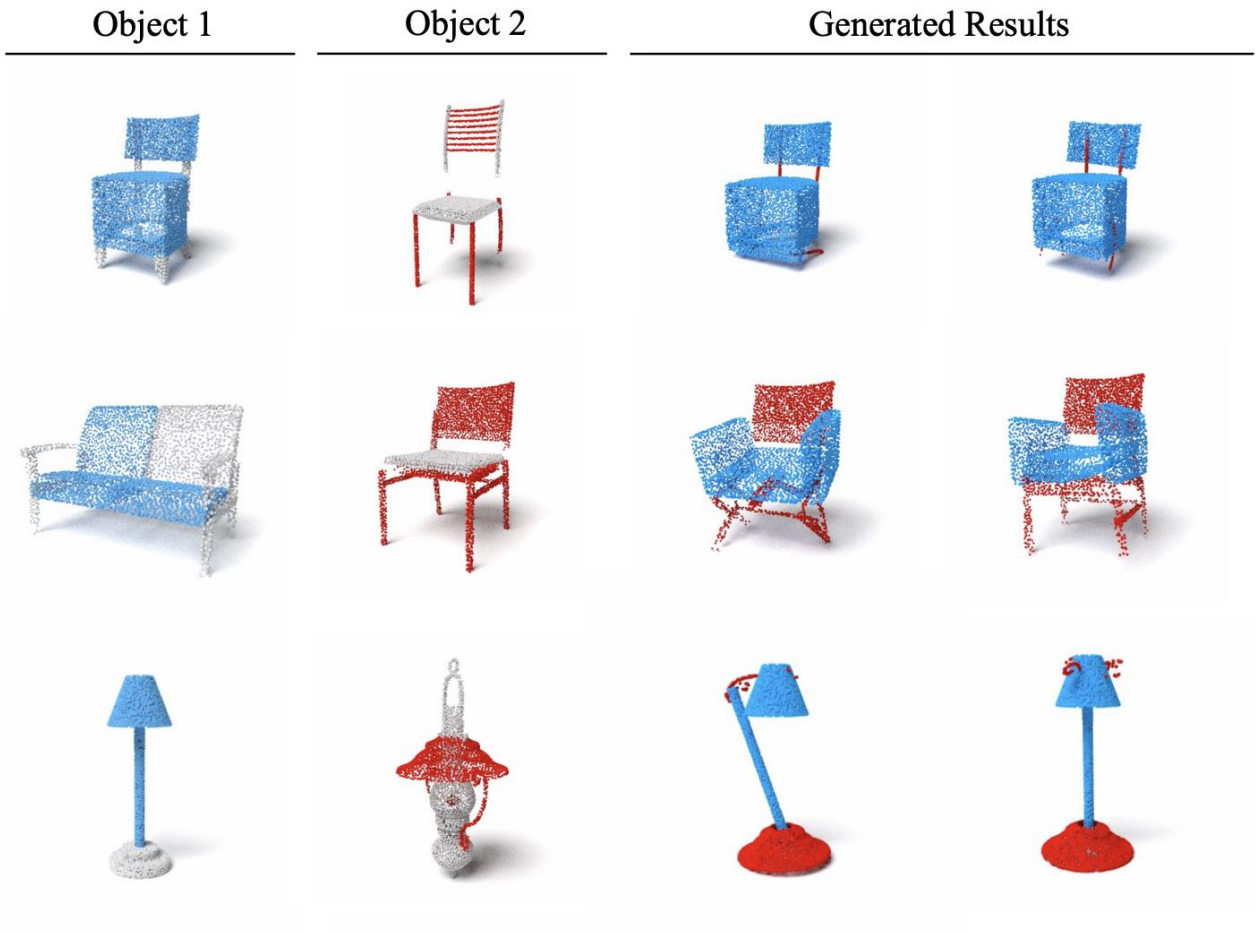
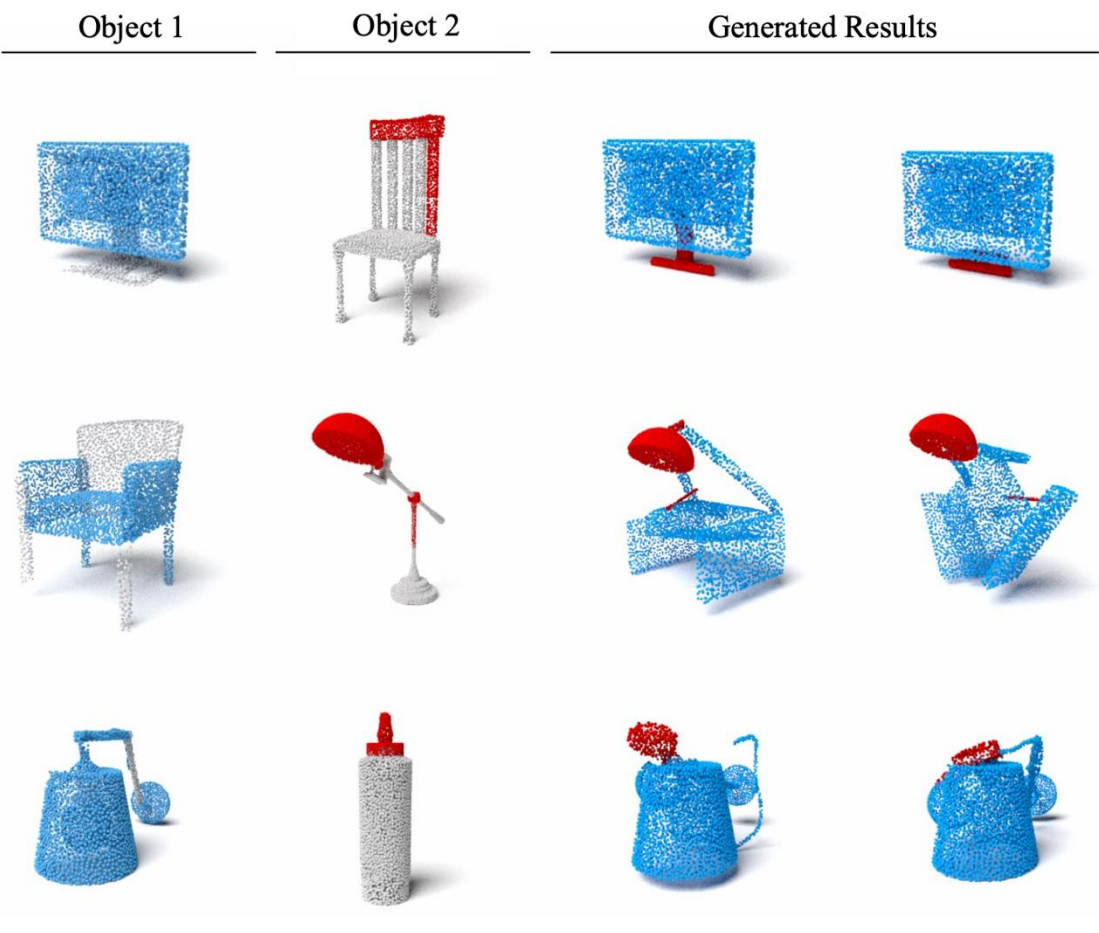


# Experiments: Pairwise Registration and Reassembly



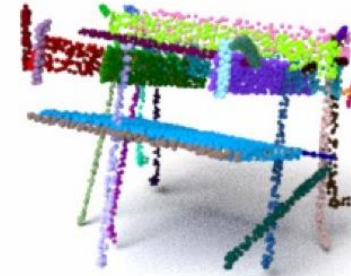


# Generating Novel Objects

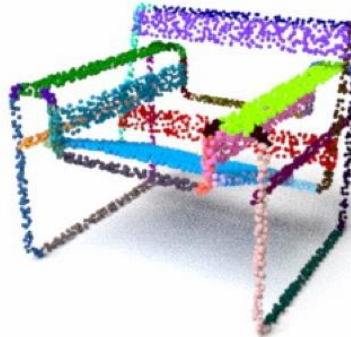


# Failure Cases

Prediction



GT



Geometrically plausible,  
but functionally incorrect.

Objects with high  
geometric complexity.

# Rectified Point Flow: Generic Point Cloud Pose Estimation

Tao Sun<sup>1,\*</sup> Liyuan Zhu<sup>1,\*</sup> Shengyu Huang<sup>2</sup> Shuran Song<sup>1</sup> Iro Armeni<sup>1</sup>

<sup>1</sup>Stanford University <sup>2</sup>NVIDIA Research (\*equal contribution)

NeurIPS 2025 • Spotlight



Paper



Code



Model



Dataset

Learning a continuous Euclidean-space point flow that  
assembles unposed parts and recovers **poses from assembled shapes**.



Homepage



GitHub

**Thu 4 Dec**  
**4:30 - 7:30 PM**

Poster Session

Homepage: [rectified-pointflow.github.io/](https://rectified-pointflow.github.io/)