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NEURAL INFORMATION PROCESSING SYSTEMS

Rectified Point Flow: Generic Point Cloud Pose Estimation

NeurIPS 2025 (Spotlight)

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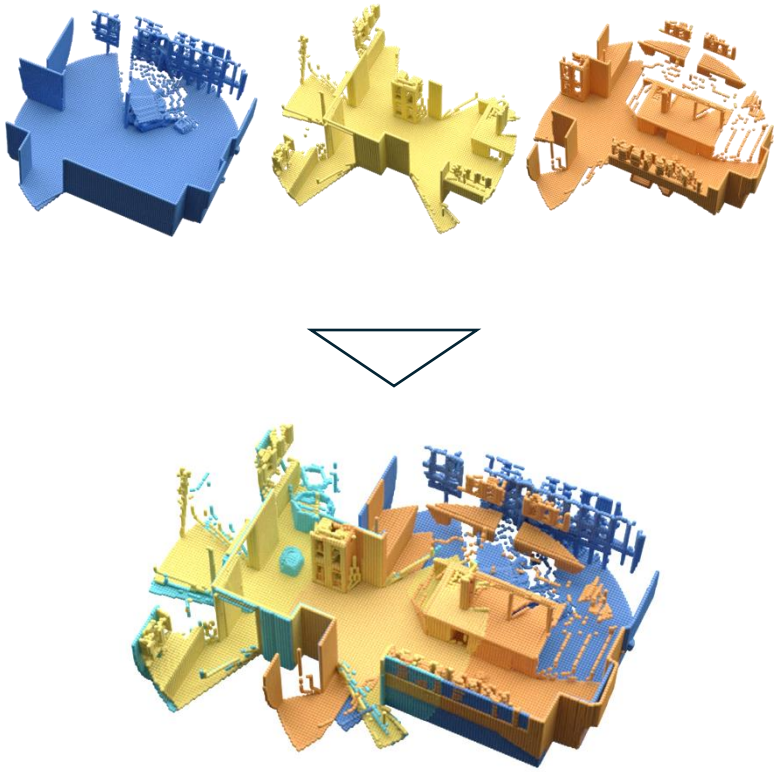
Shuran Song, Iro Armeni

Why Pose Estimation?

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

Point Cloud Registration	Fragments Reassembly	Robotic Assembly

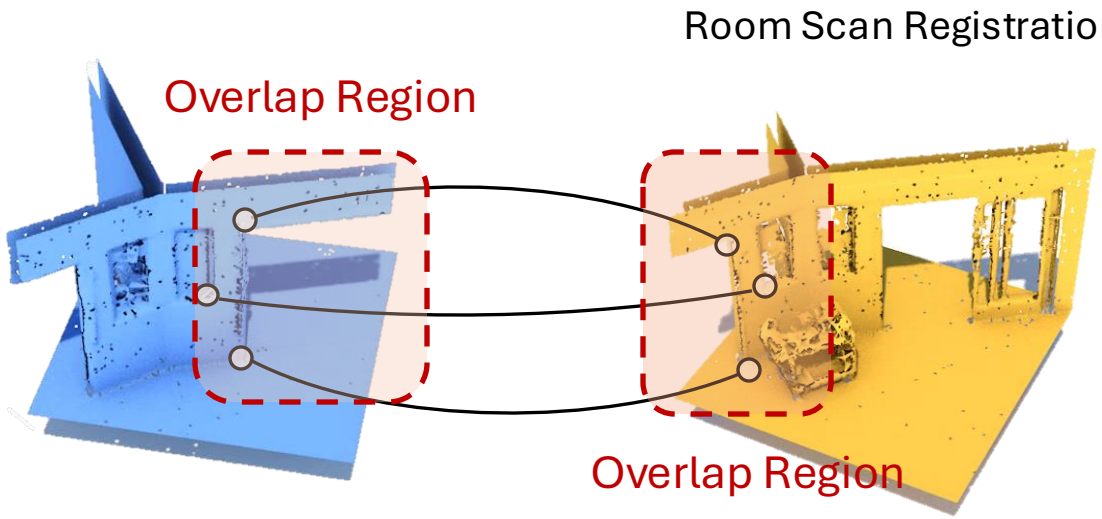


Figures from GARF

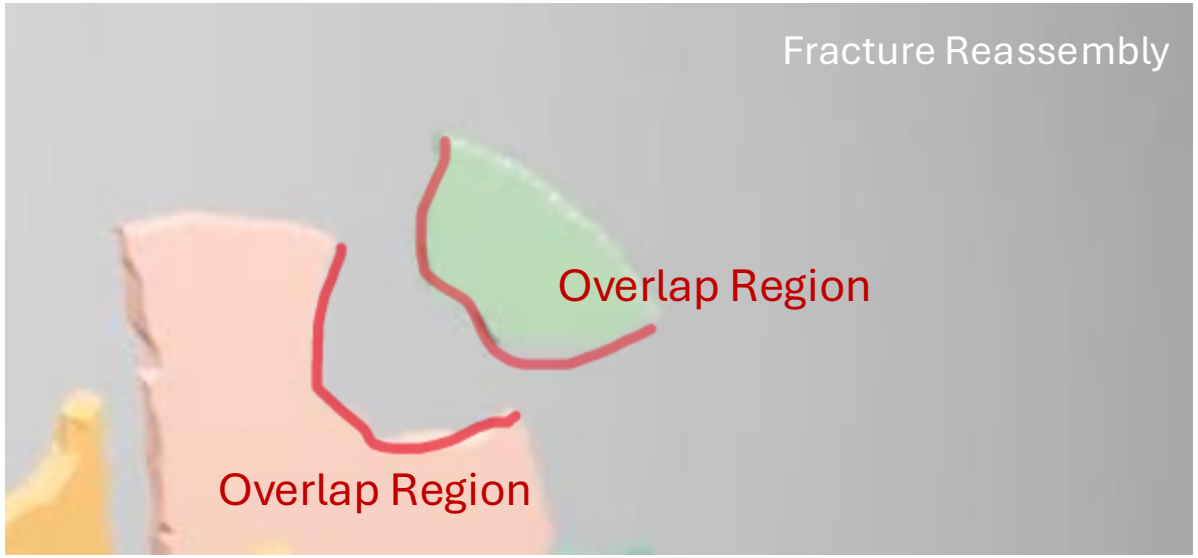
Why Pose Estimation Can Be Hard?

1. Most registration methods rely on correspondence pairs.

Enough Overlap	Not Enough Overlap



Overlap Ratio > 10%

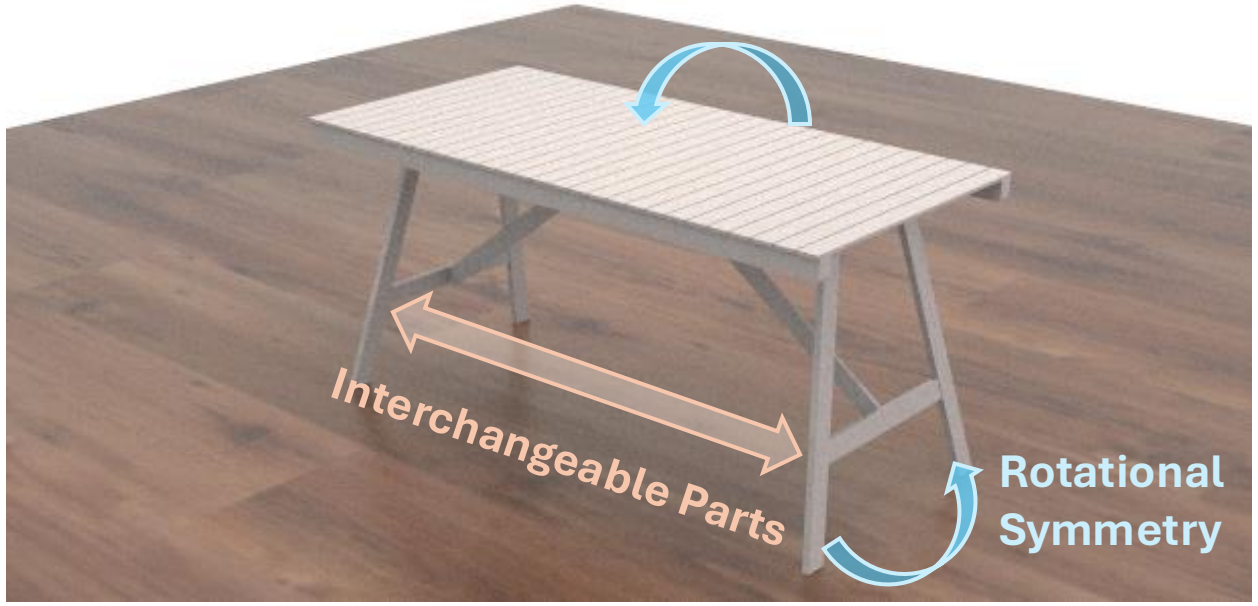


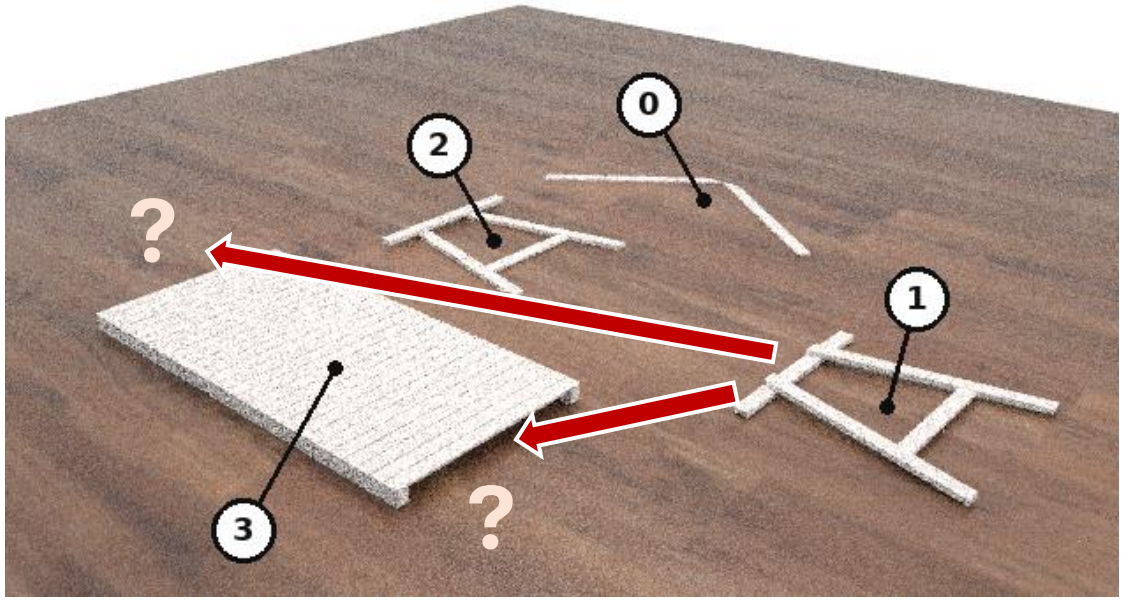
Overlap Ratio < 1%

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

Why Pose Estimation Can Be Hard?

2. Part-level symmetry further complicates the issue.





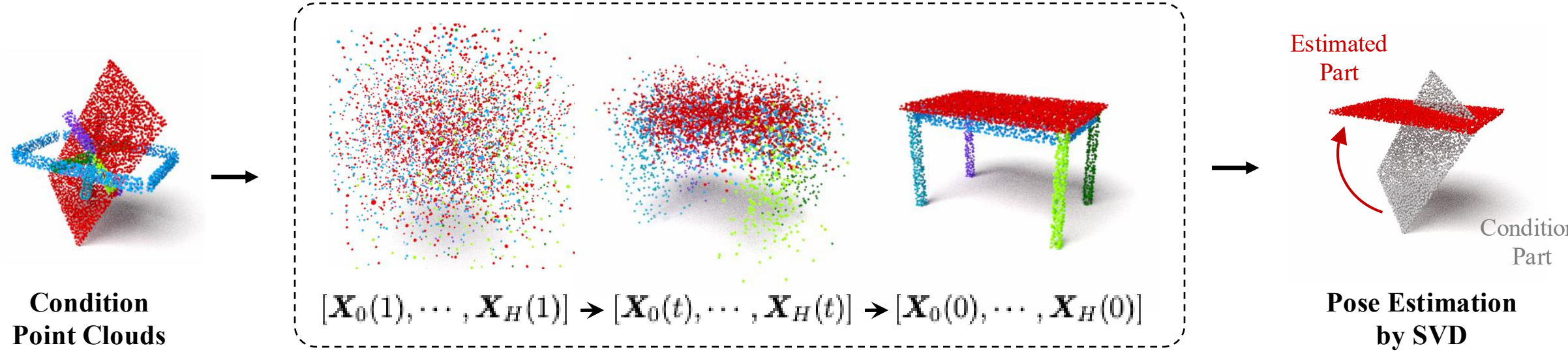
Multiple Plausible Configurations Exists

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

Our Solution: Pose from Shape

First shape, then pose.

A Euclidean-space Flow

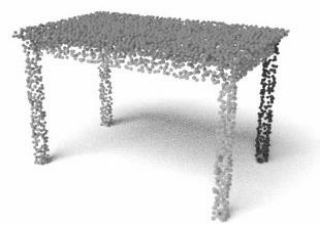


Shape is independent of **correspondence** and encodes all the **symmetry** information.

Overlap-aware Pretraining

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

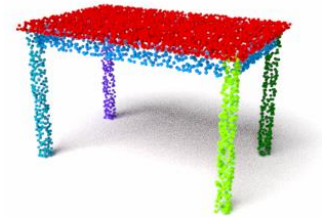
Input Object



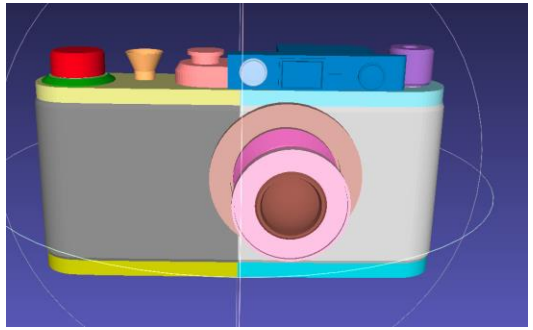
PartField

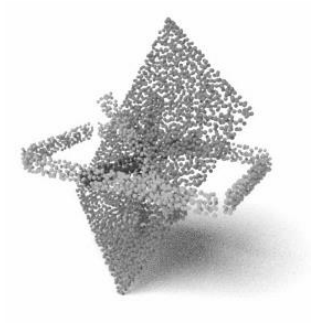
Frozen

Segmented Parts



Distilling knowledge from **3D segmentation models.**

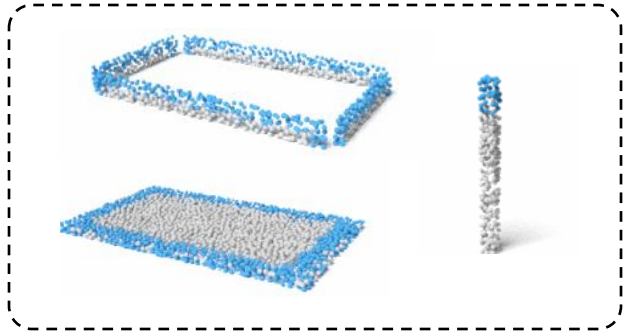




Unposed Parts

Point Encoder

Training



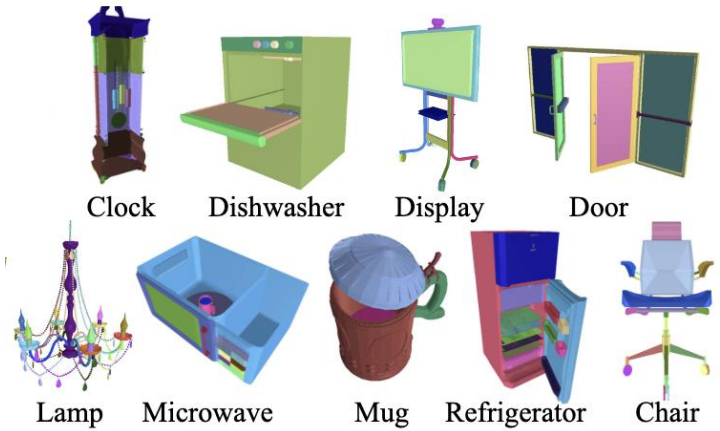
Overlap Labels

[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

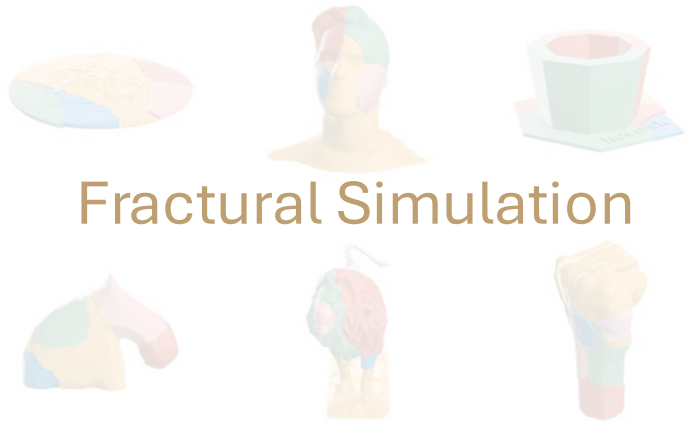
PartNet

Semantics and Function

IKEA-Manual

Reusability and Packing Efficiency

BreakingBad



Fractural Simulation

TwoByTwo

Insertable Parts

TUD-L

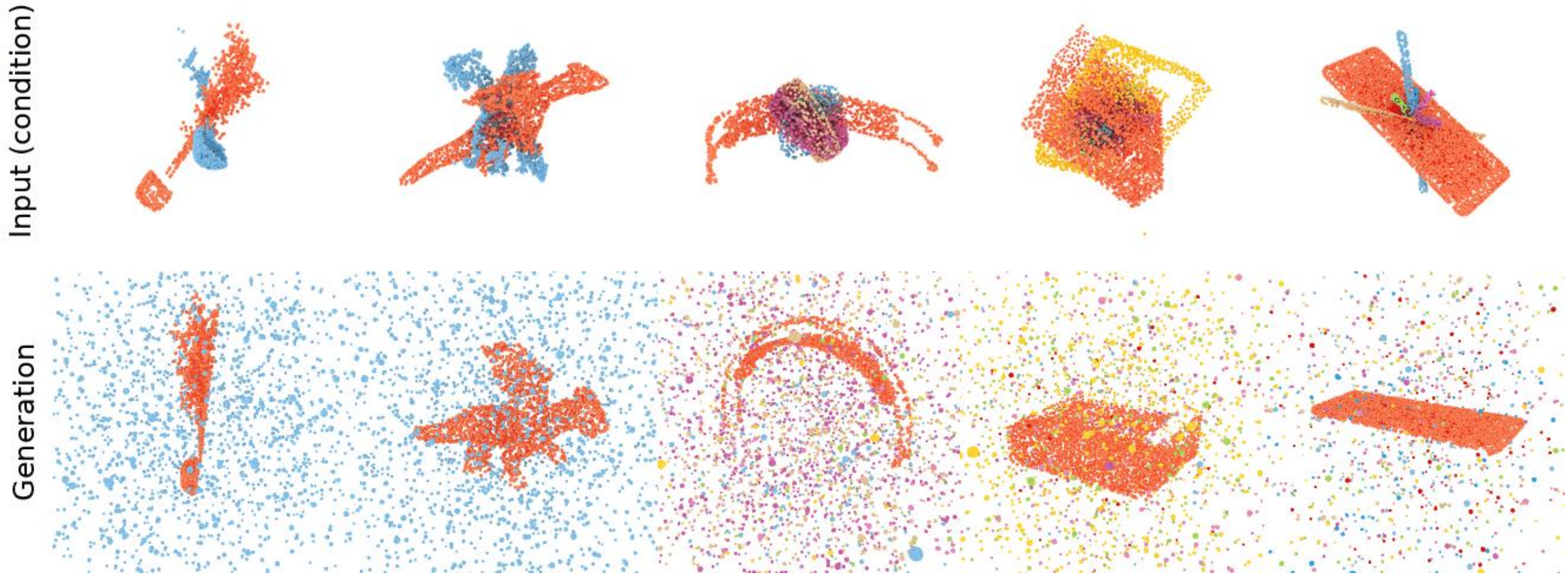
Real RGBD Scan

ModelNet-40

Random Plane Cropping

Flow Trajectories

Assembly prediction given unposed parts

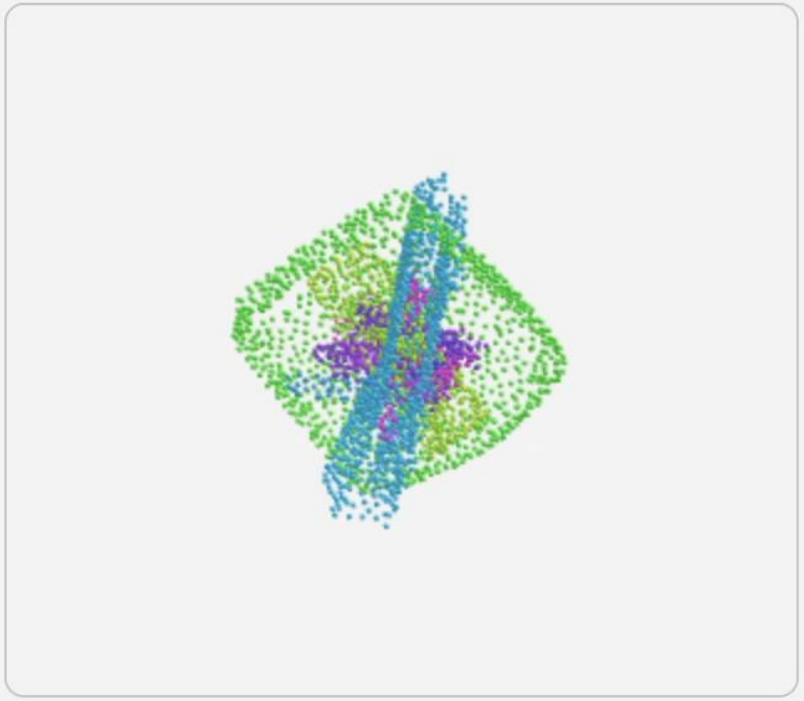


Flow Trajectories

Assembly prediction given unposed parts

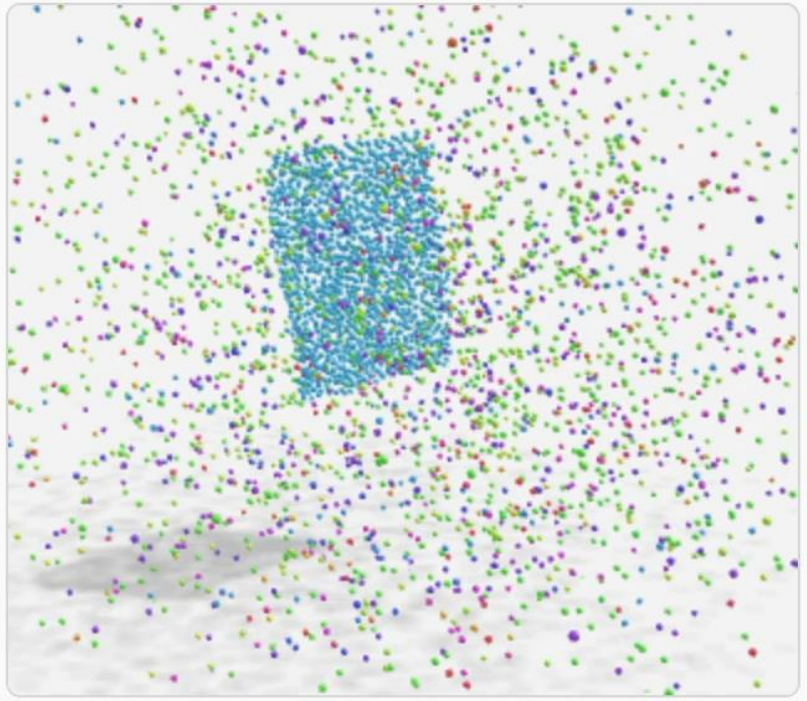
Condition

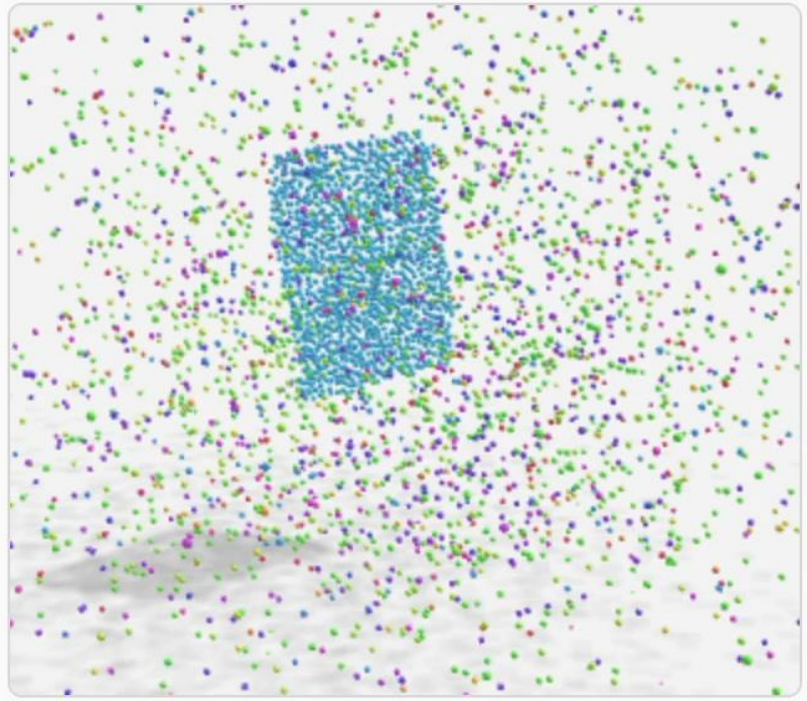
Unposed Part Point Clouds



Generation

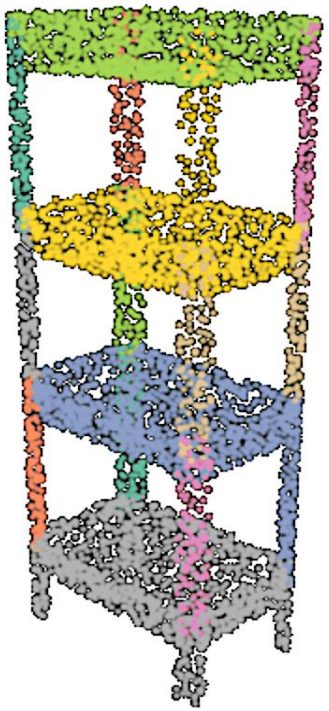
Possible Assembled Point Clouds



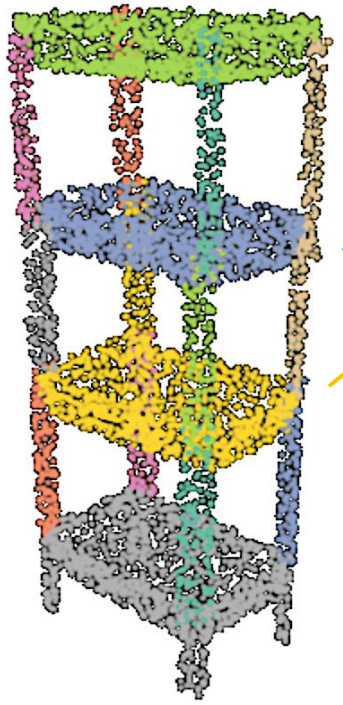


Learning Part Symmetry by Construction

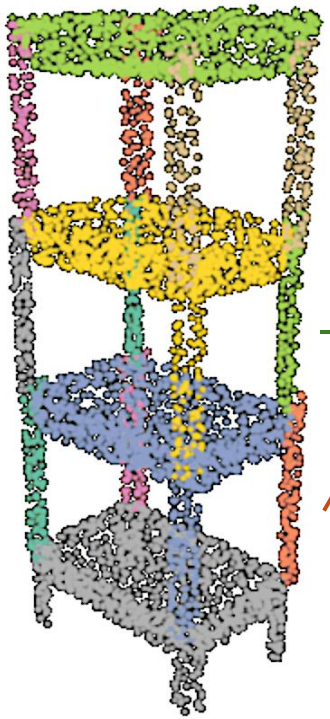
Without any symmetry labels



Ground Truth



Generated Result 1



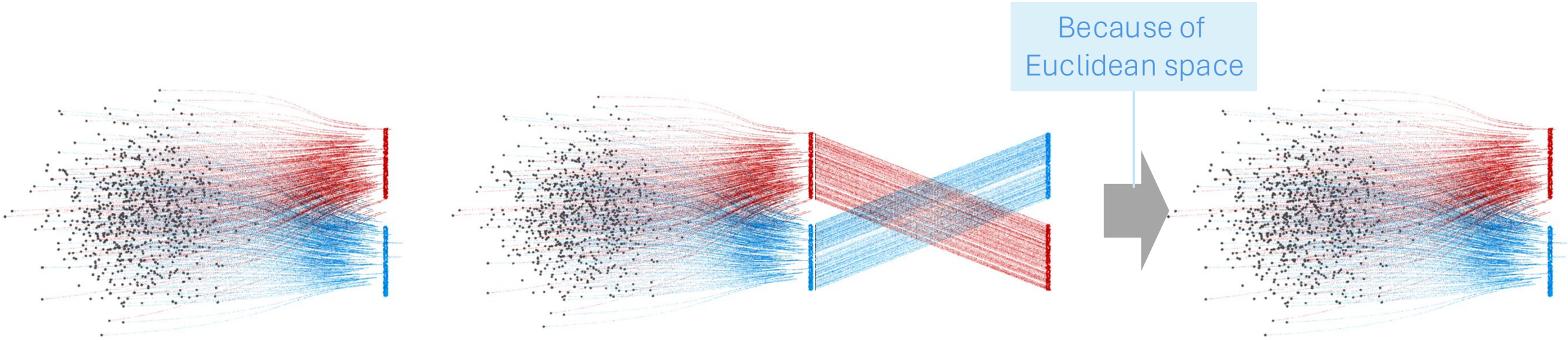
Generated Result 2

Generated Result 3

Model swaps 2 middle baskets and 12 vertical bars.

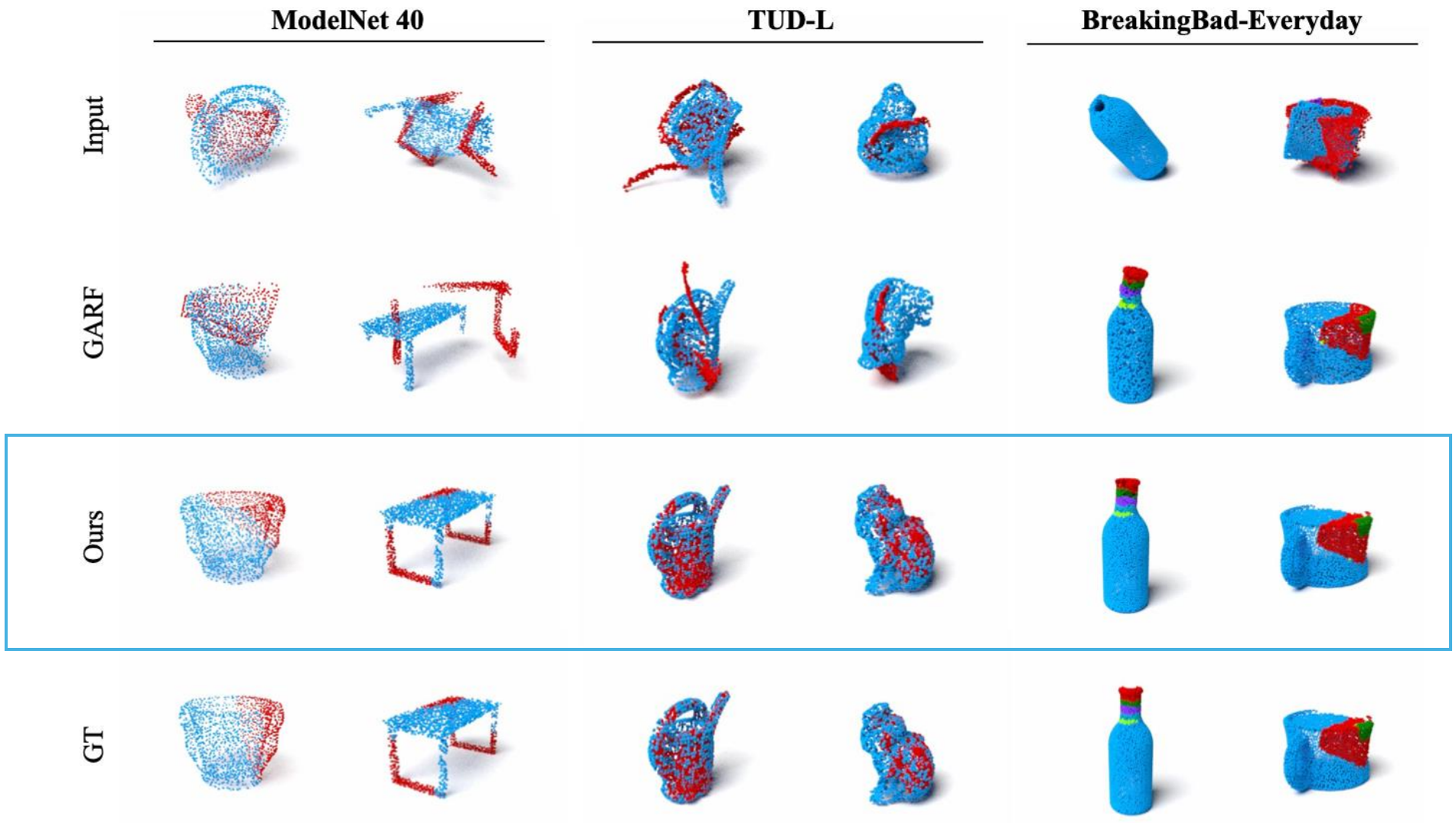
Learning Part Symmetry by Construction

For part interchangeability and arbitrary part segmentation

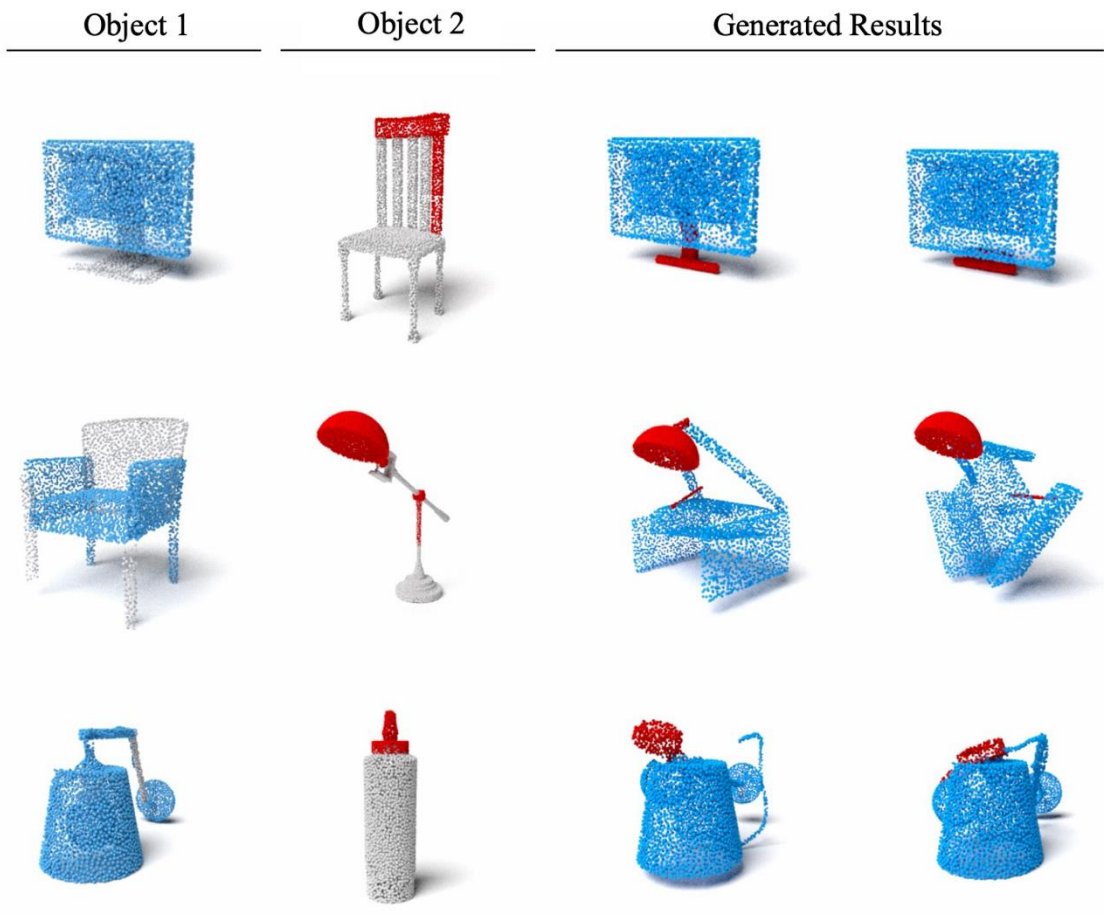


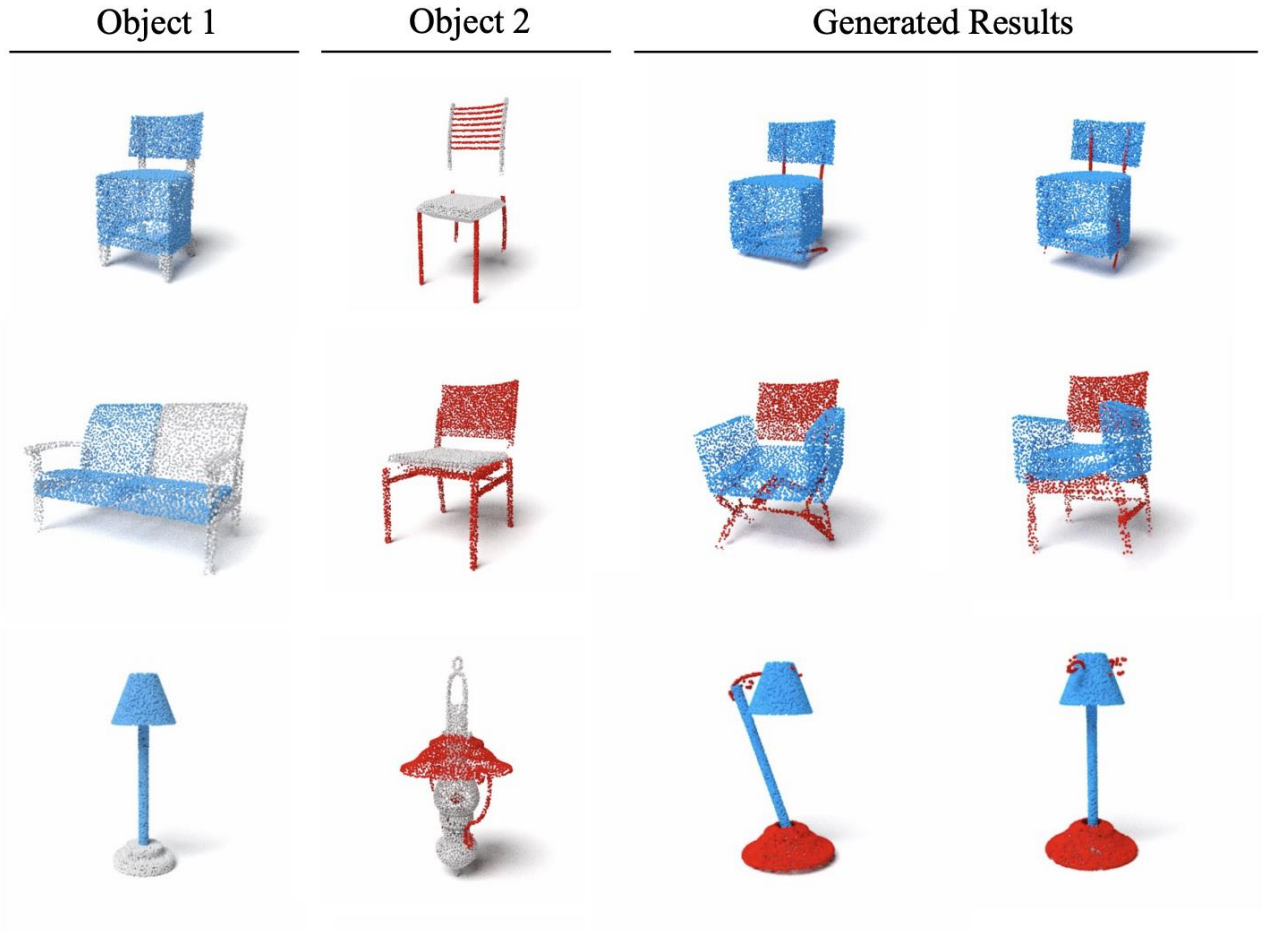
Experiments: Shape Assembly

Experiments: Pairwise Registration and Reassembly

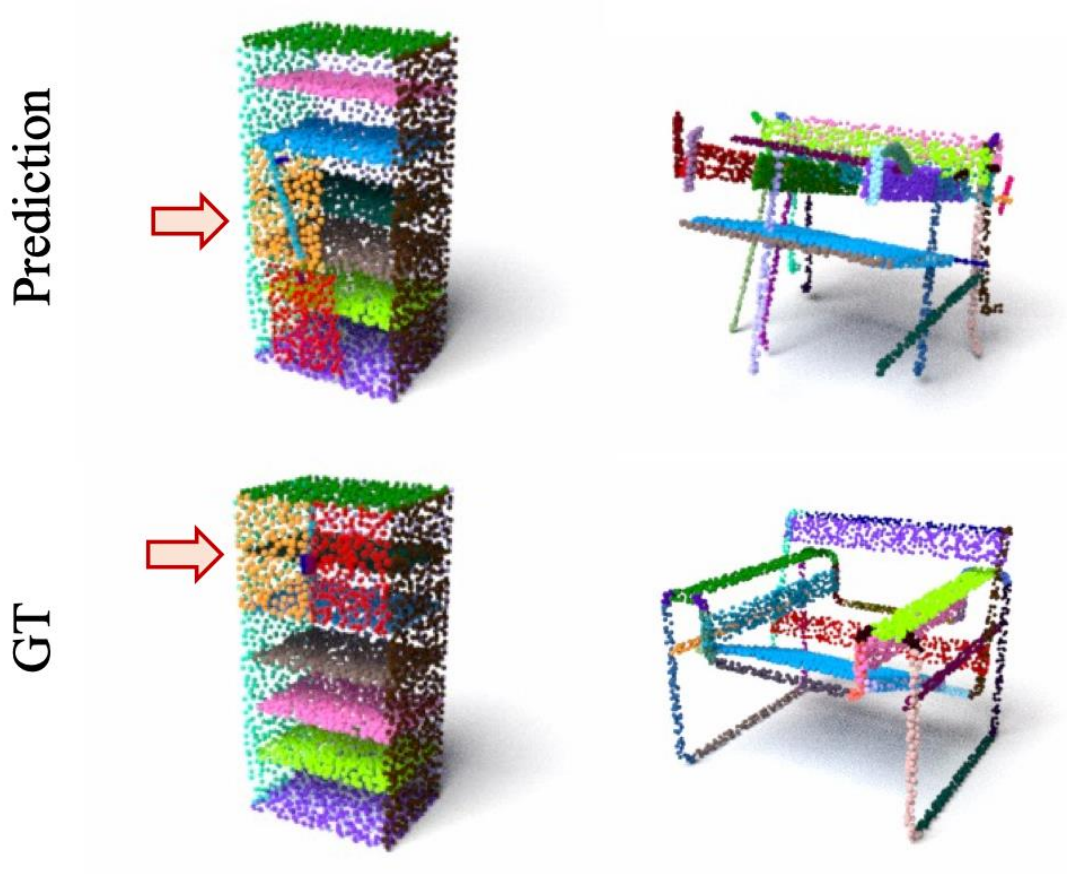


Generating Novel Objects





Failure Cases



Geometrically plausible, but functionally incorrect.

Objects with high geometric complexity.

Stanford University

Gradient Spaces

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[1]Stanford University [2]NVIDIA Research ([*]equal contribution)

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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/