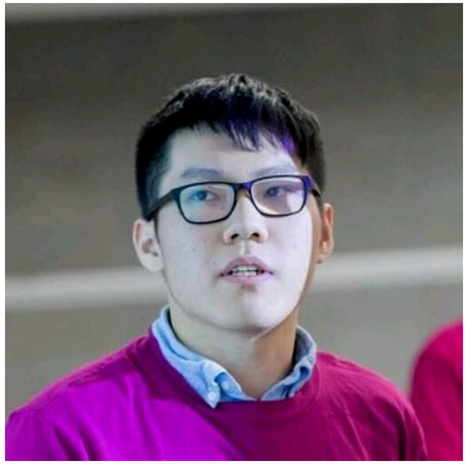
Neural Shape Mating: Self-Supervised Object Assembly with Adversarial Shape Priors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UNIVERSITY OF TORONTO

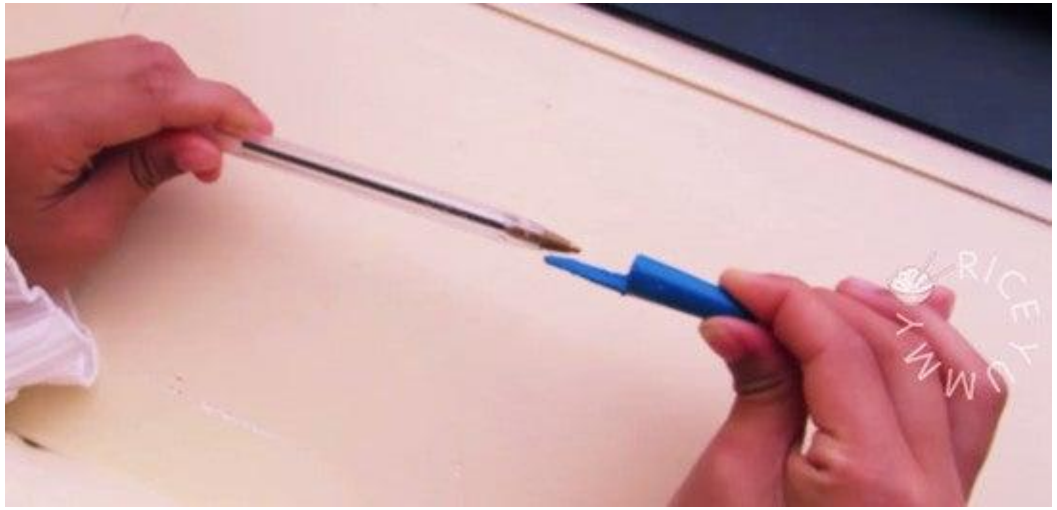
VECTOR INSTITUTE

NVIDIA

Adobe

3D Shape Assembly

Plug and Socket



Pen and Cap

Pot and Lid

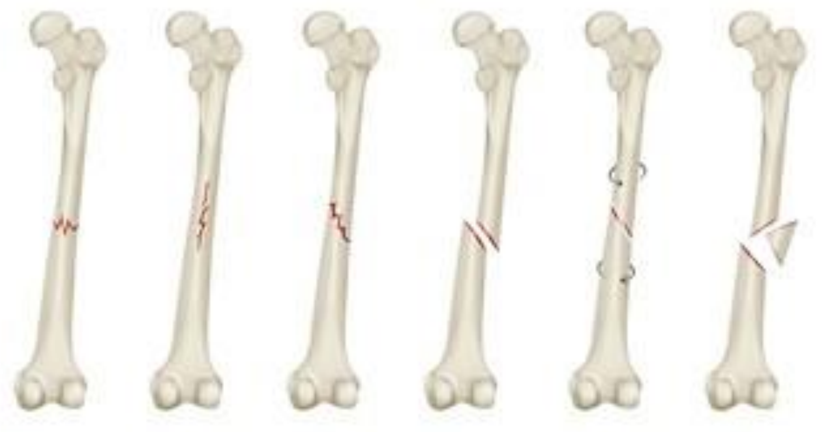
Toothbrush and Case

3D Geometric Shape Assembly

Broken vase

Broken sculpture

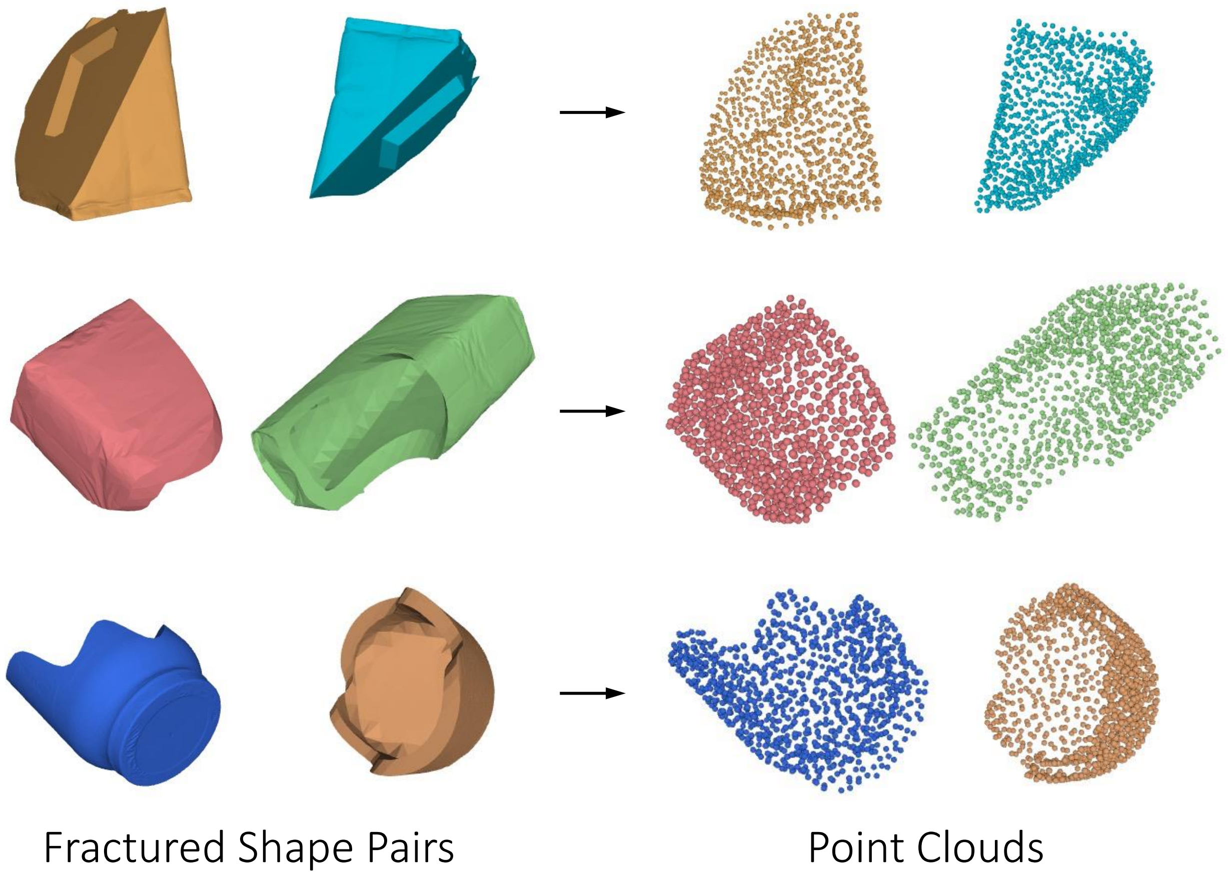
Broken fossil



Broken bones

Pairwise 3D Geometric Shape Assembly

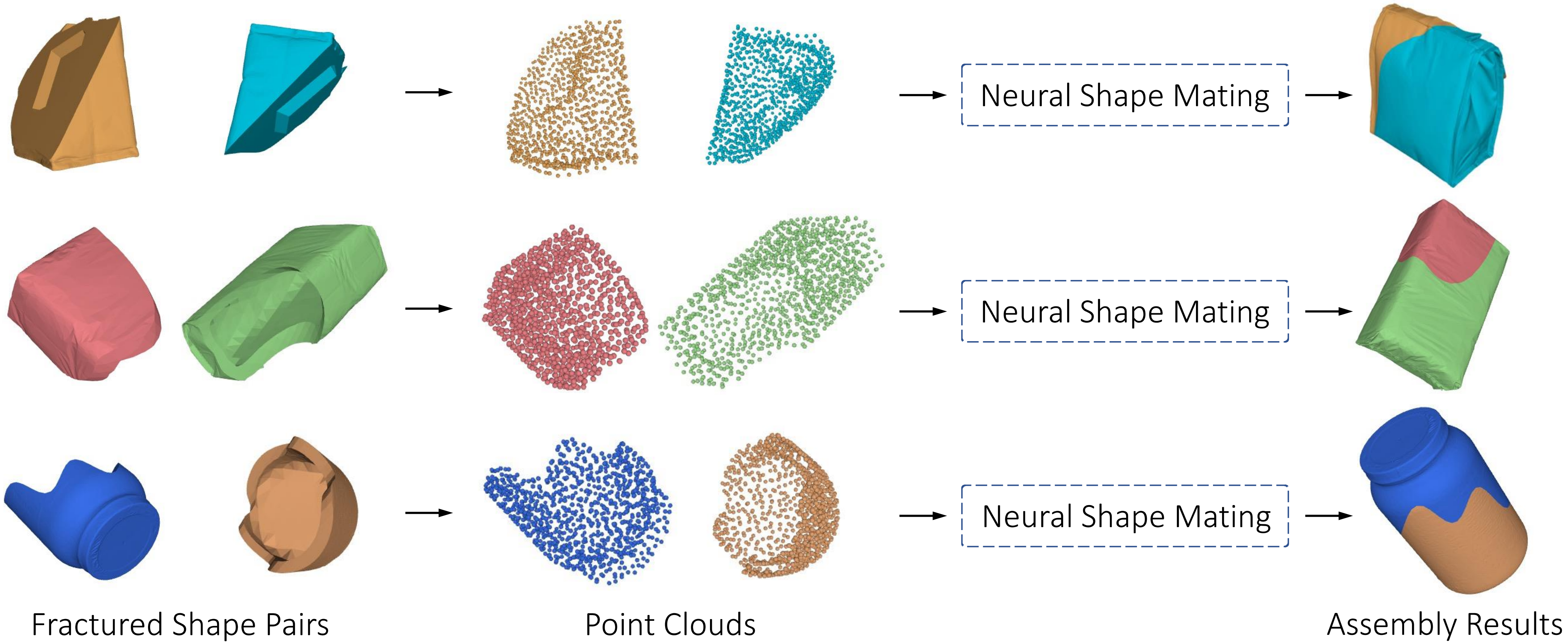
Input: Two shapes



Pairwise 3D Geometric Shape Assembly

Input: Two shapes

Goal: Develop an algorithm that learns to assemble them



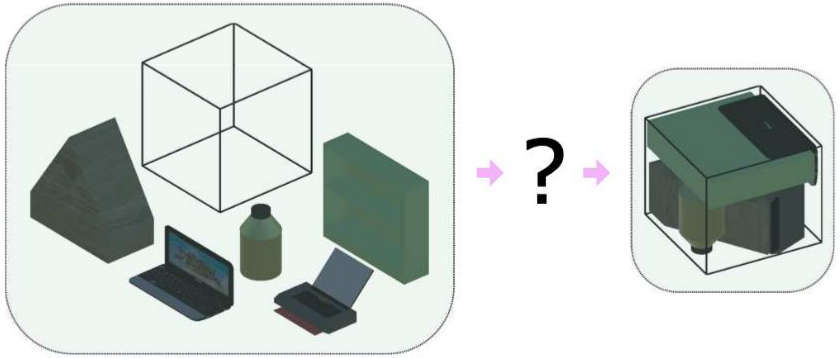
Applications

Furniture Assembly

Pick and Place

Object Kitting

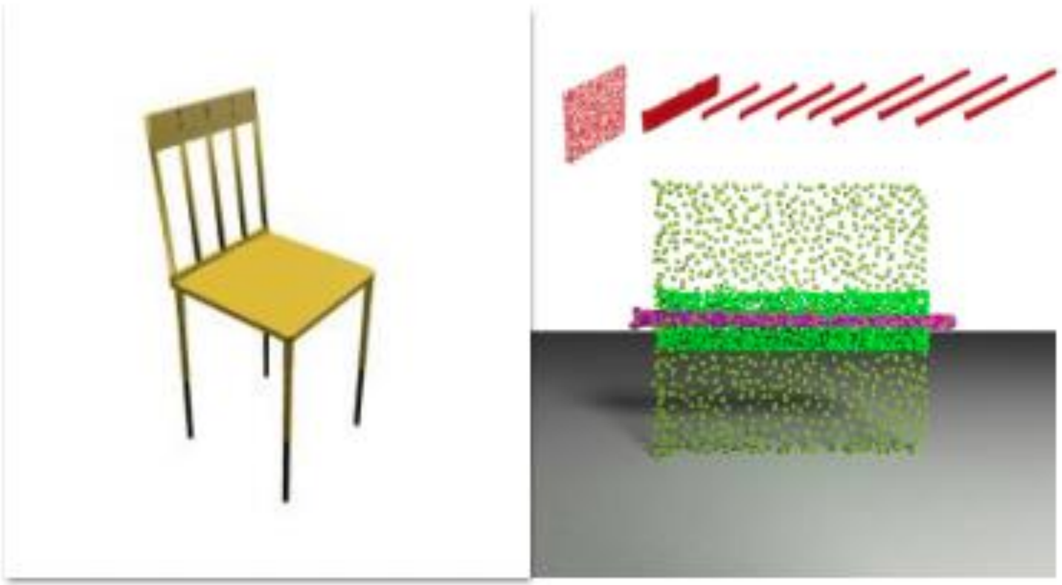
Toy Assembly



Object Packing

Semantic Shape Assembly

Input: A set of part point clouds and a target shape

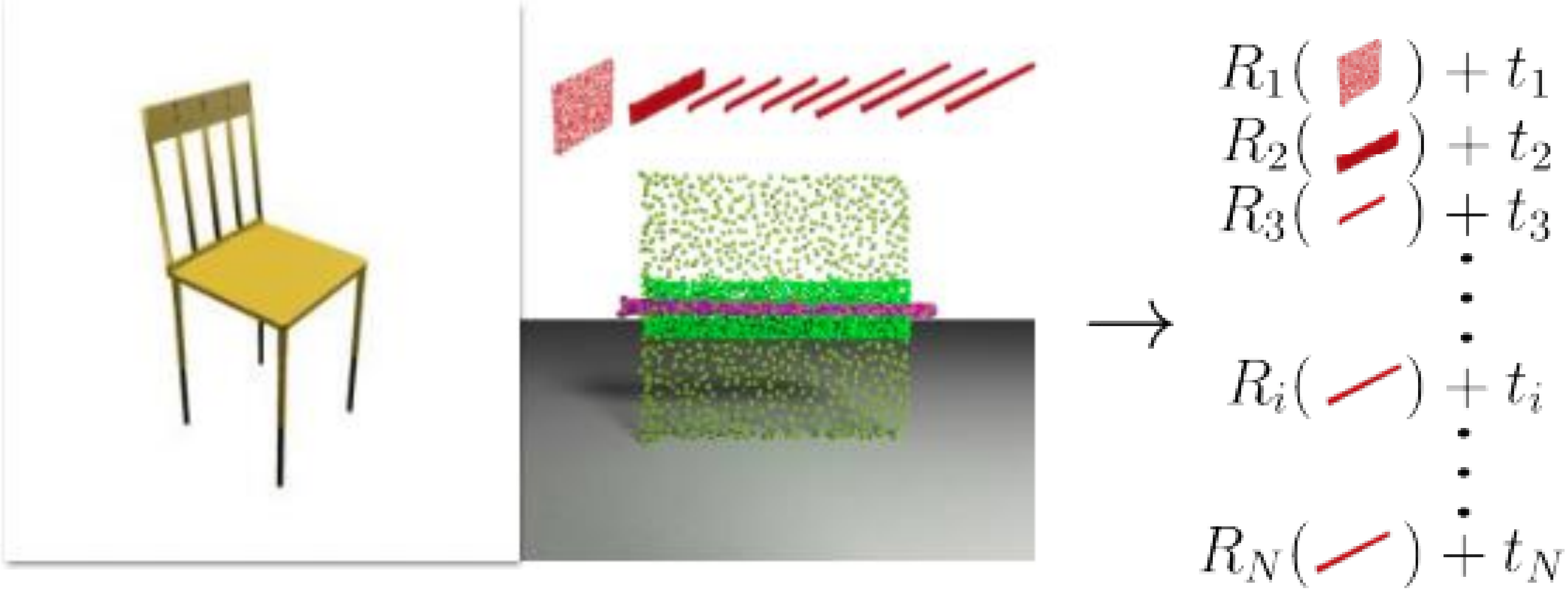


Target Shape Part Point Clouds

Semantic Shape Assembly

Input: A set of part point clouds and a target shape

Idea: Formulate shape assembly as a part pose prediction problem

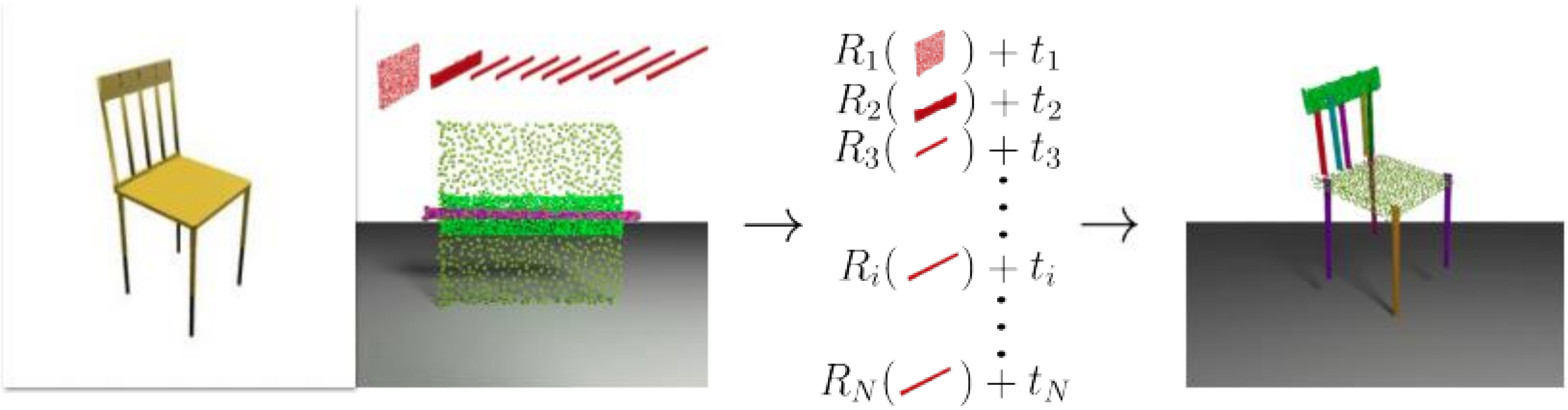


Target Shape Part Point Clouds Pose Predictions

Semantic Shape Assembly

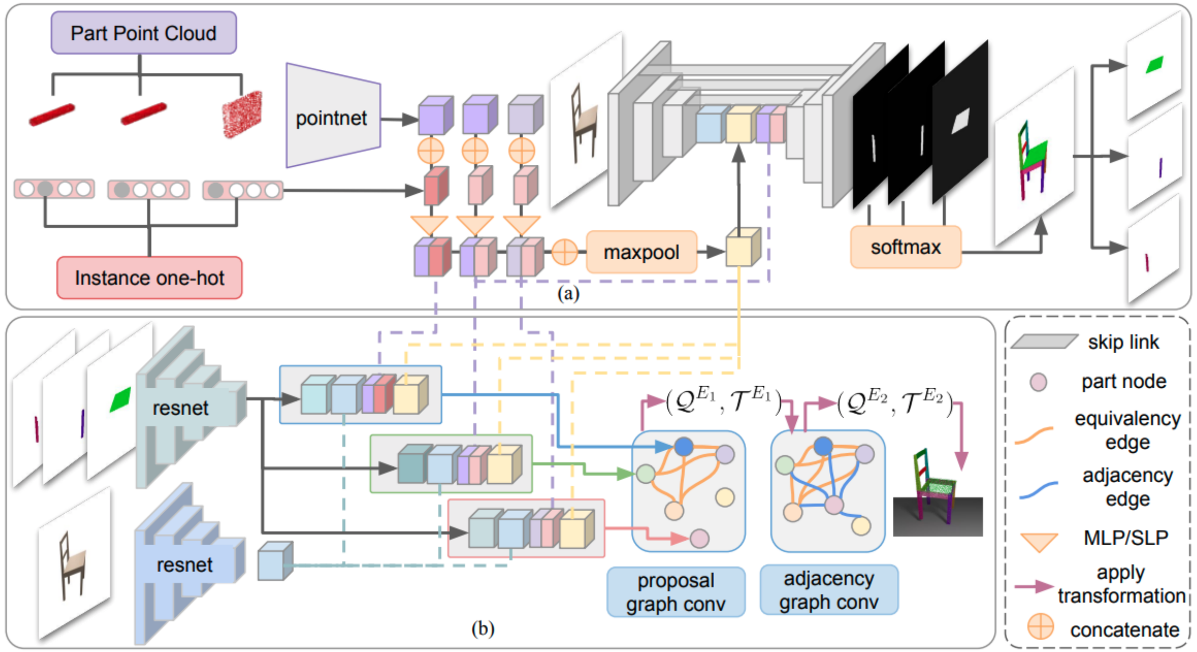
Input: A set of part point clouds and a target shape

Idea: Formulate shape assembly as a part pose prediction problem

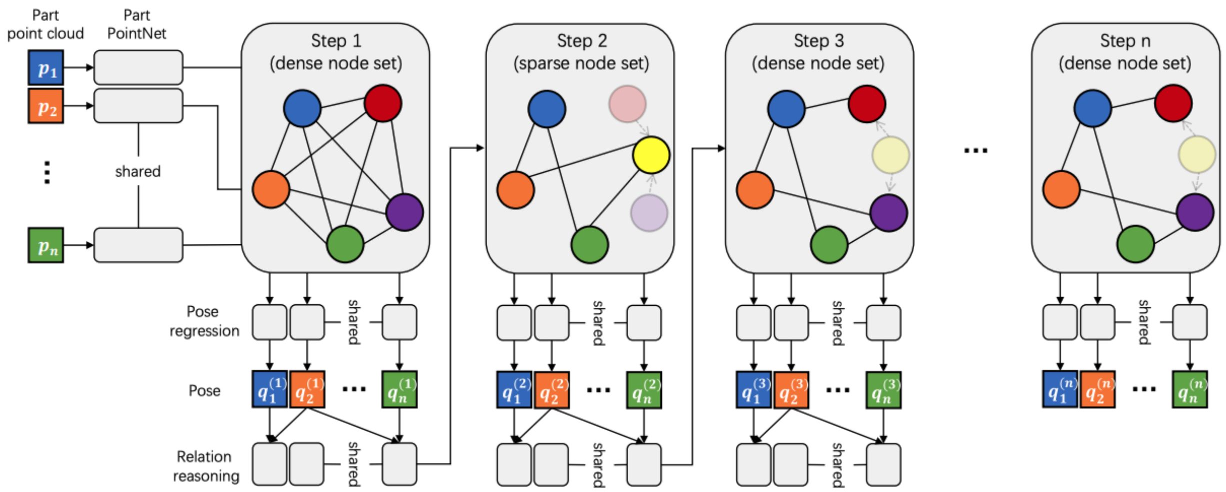


Target Shape Part Point Clouds Pose Predictions Assembly Result

Prior Work: Semantic Shape Assembly



[Li et al. ECCV 2020]



[Huang et al. NeurIPS 2020]

+ Part segmentation as guidance
+ Graph networks for inferring part relationships

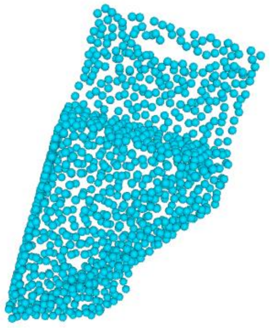
- Part segmentation ground truth
- Part pose ground truth

+ No need part segmentation
+ Graph networks for inferring part relationships
+ Coarse-to-fine pose refinement

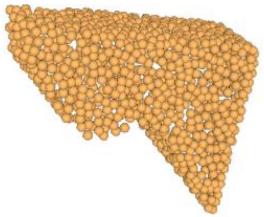
- Part pose ground truth

Method: Neural Shape Mating

Input: Two point clouds P_A and P_B



P_A

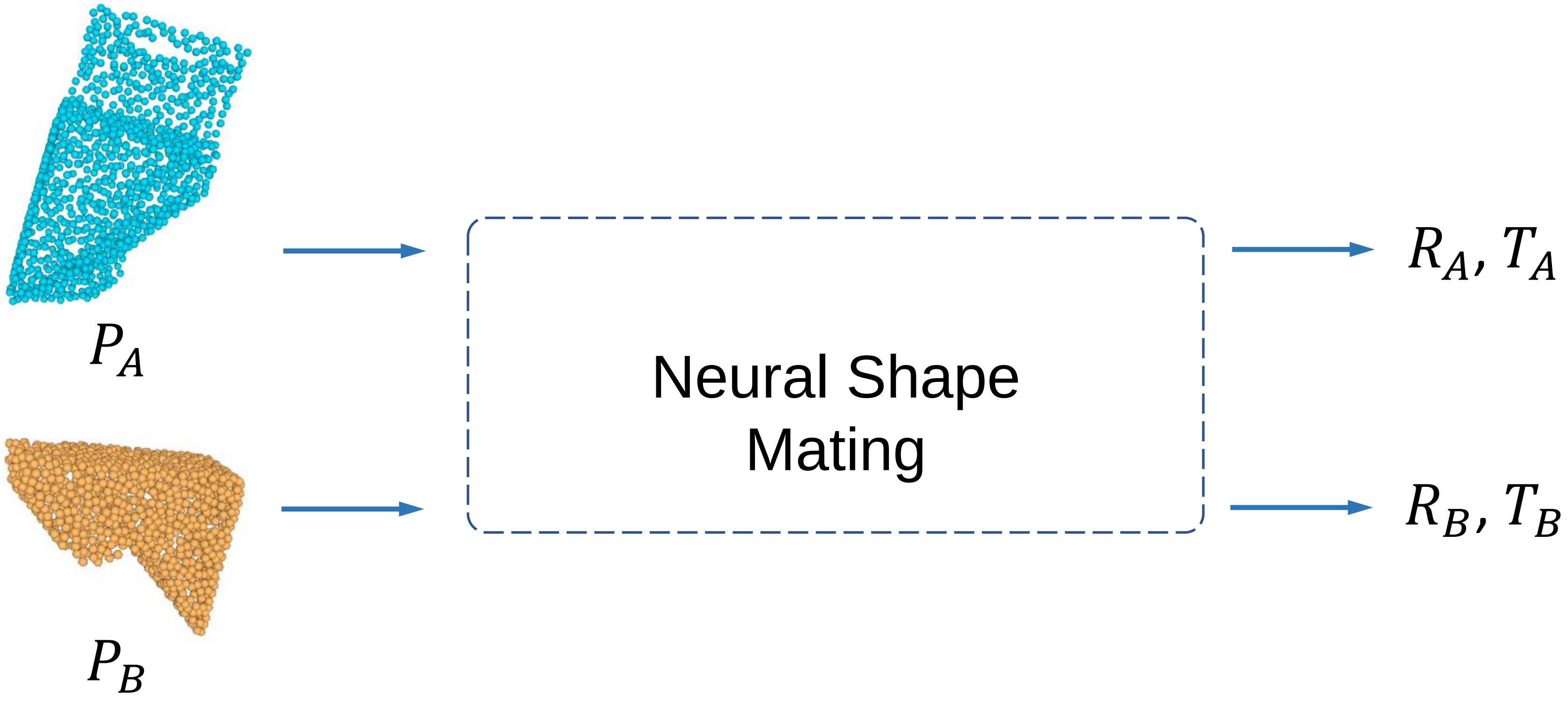


P_B

Method: Neural Shape Mating

Input: Two point clouds P_A and P_B

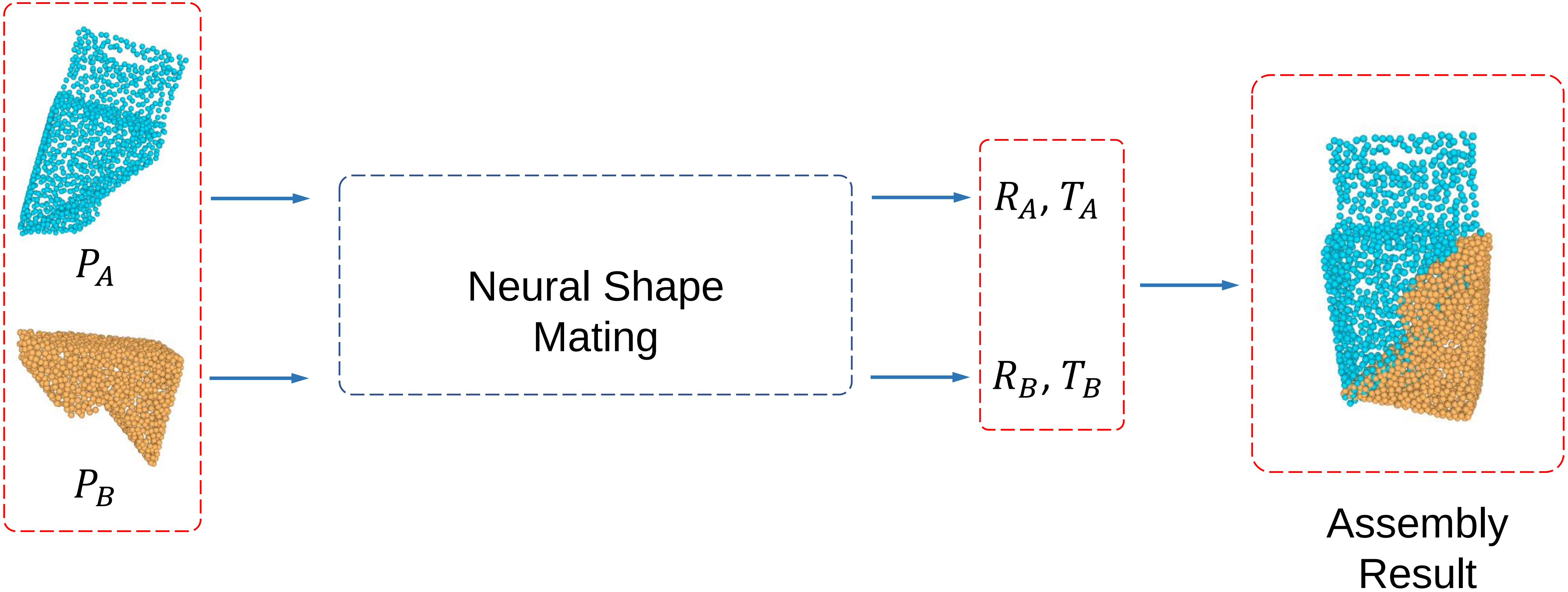
Output: SE(3) poses for P_A and P_B



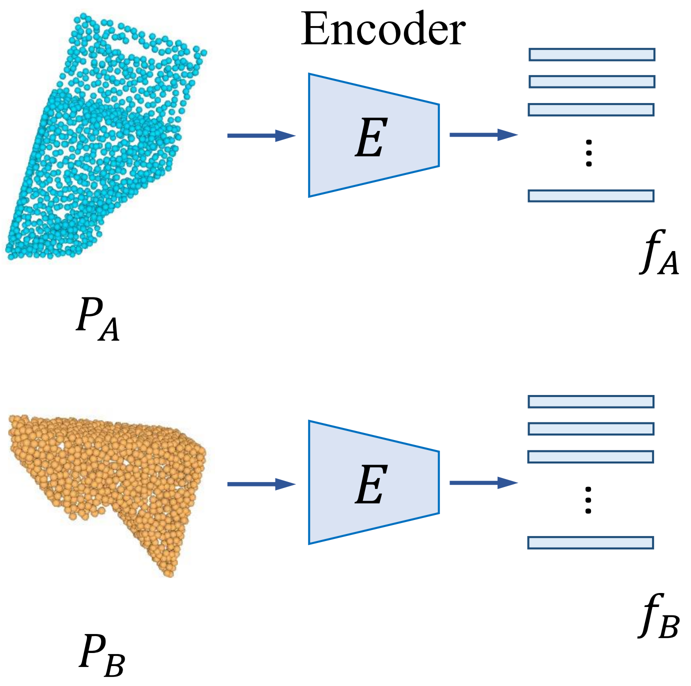
Method: Neural Shape Mating

Input: Two point clouds P_A and P_B

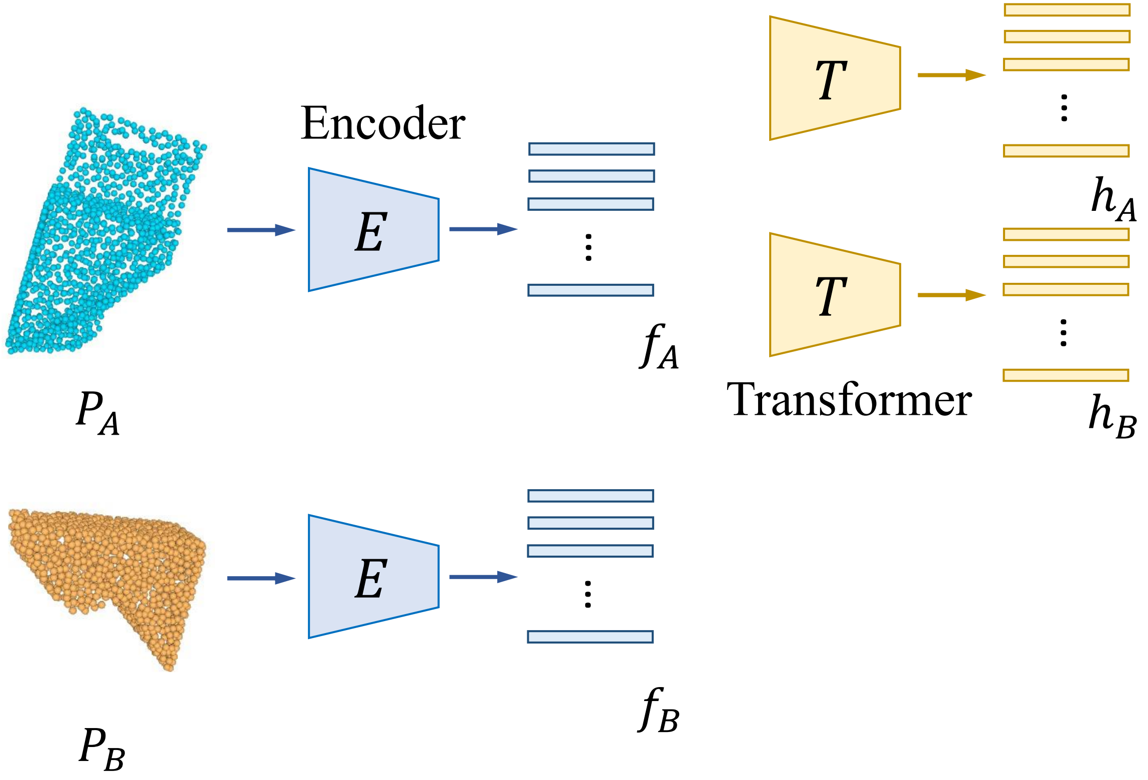
Output: SE(3) poses for P_A and P_B



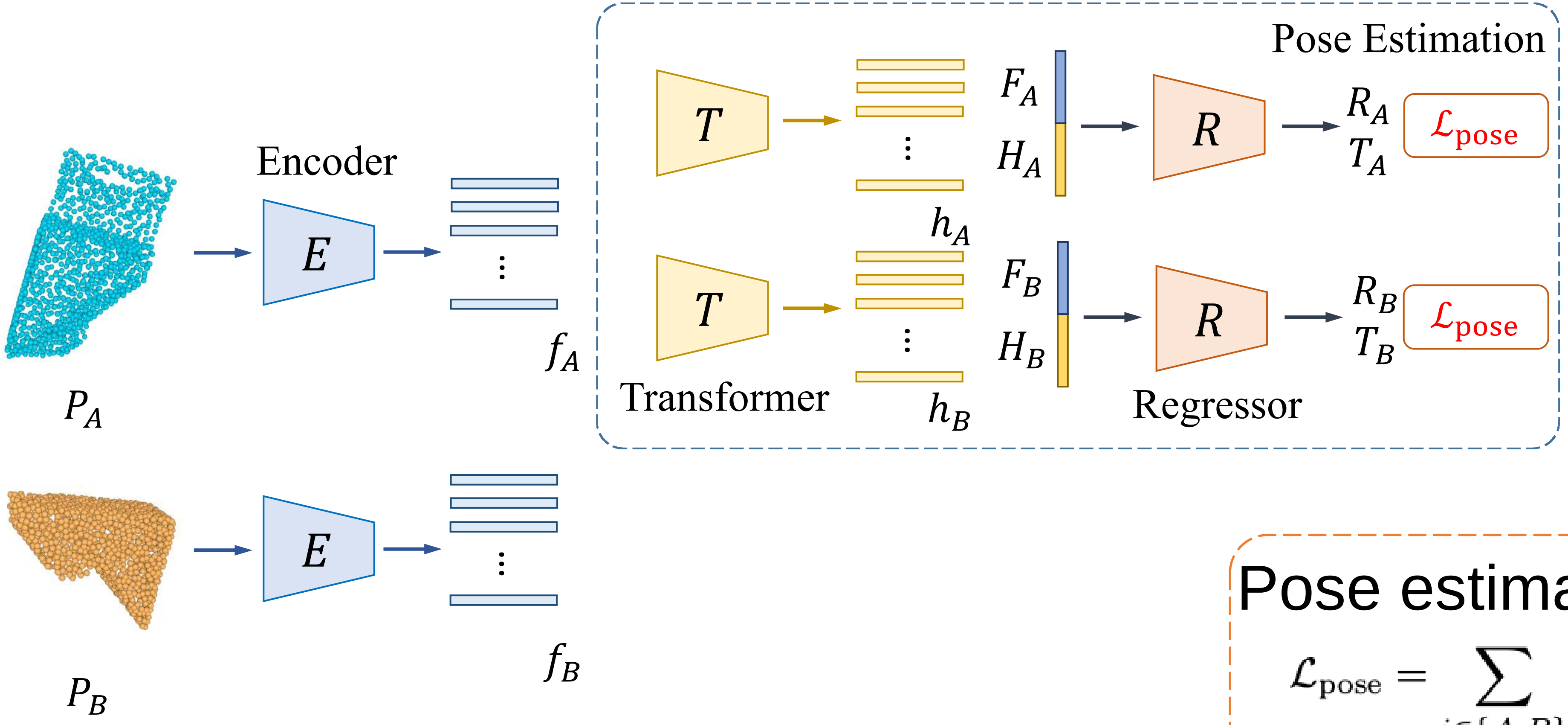
Point Feature Extraction



Cross-Shape Correlations



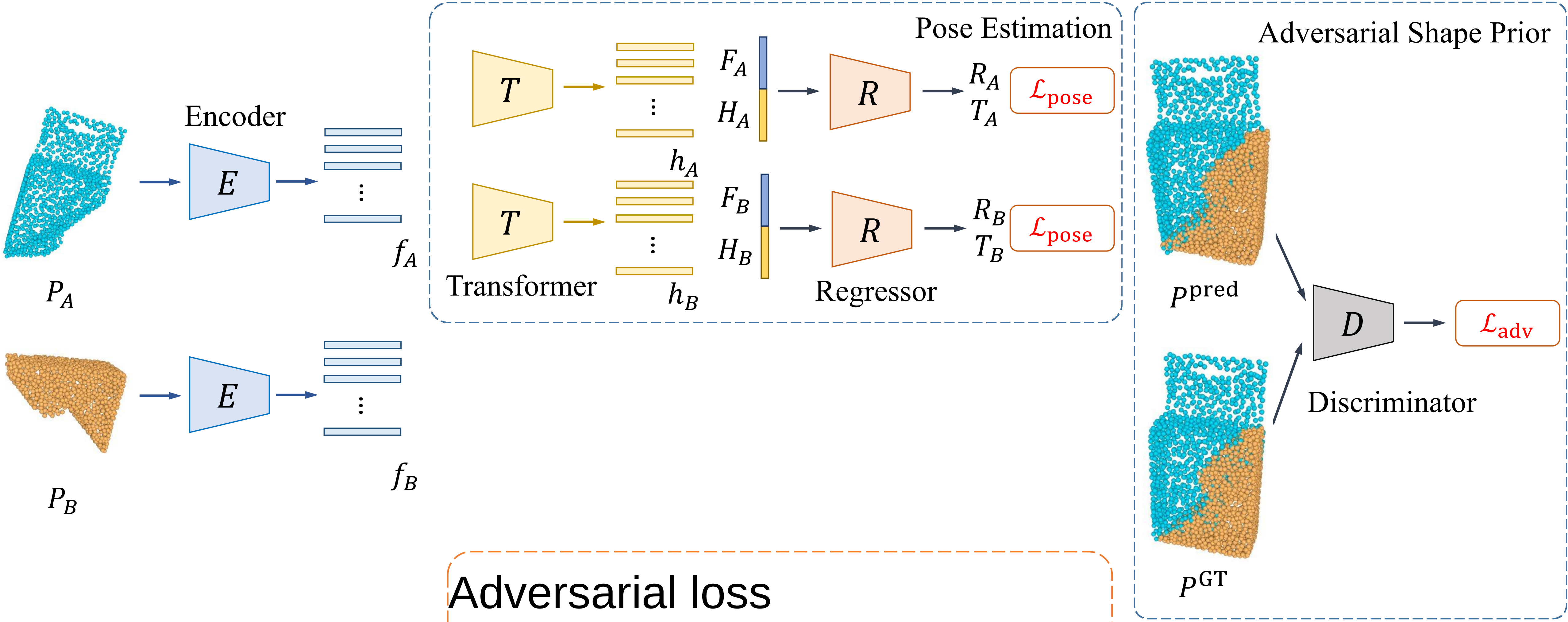
Pose Estimation for Shape Assembly



Pose estimation loss

$$\mathcal{L}_{\text{pose}} = \sum_{i \in \{A,B\}} \|R_i^\top R_i^{\text{GT}} - I\| + \|T_i - T_i^{\text{GT}}\|$$

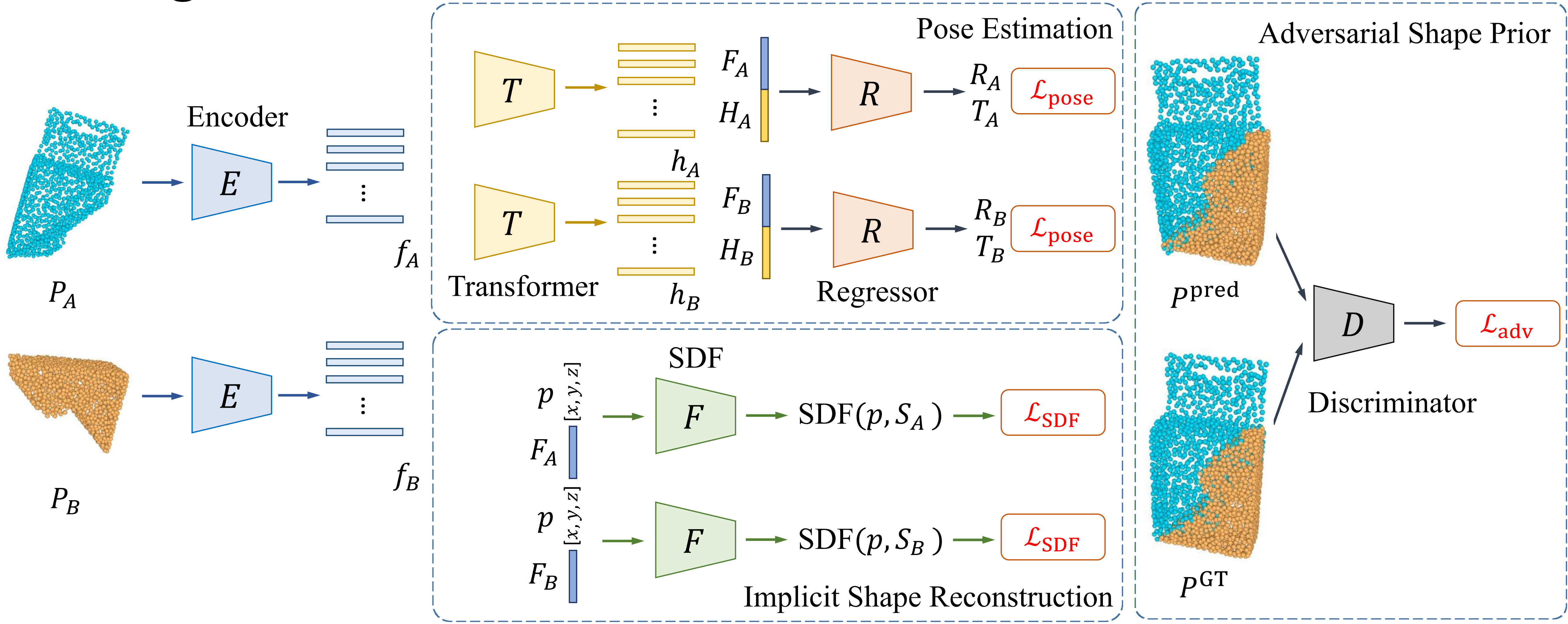
Adversarial Learning of Shape Priors



Adversarial loss

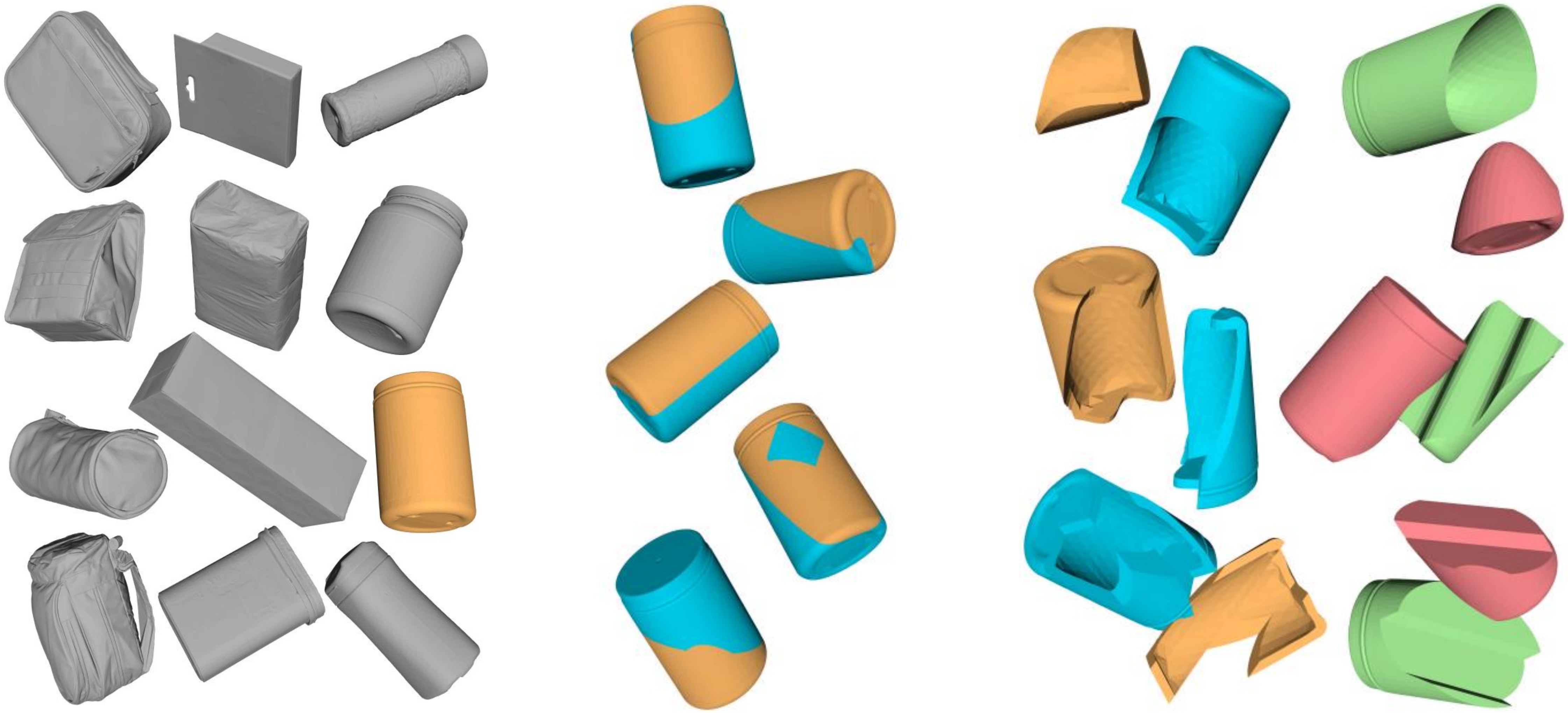
$$\mathcal{L}_{\text{adv}} = \mathbb{E}[\|D(P^{\text{pred}})\|] + \mathbb{E}[\|D(P^{\text{GT}}) - 1\|]$$

Implicit Shape Reconstruction as a Regulatization



SDF regression loss $\mathcal{L}_{\text{SDF}} = \sum_{i \in \{A,B\}} \|\text{SDF}(p, S_i) - \text{SDF}^{\text{GT}}(p, S_i)\|$

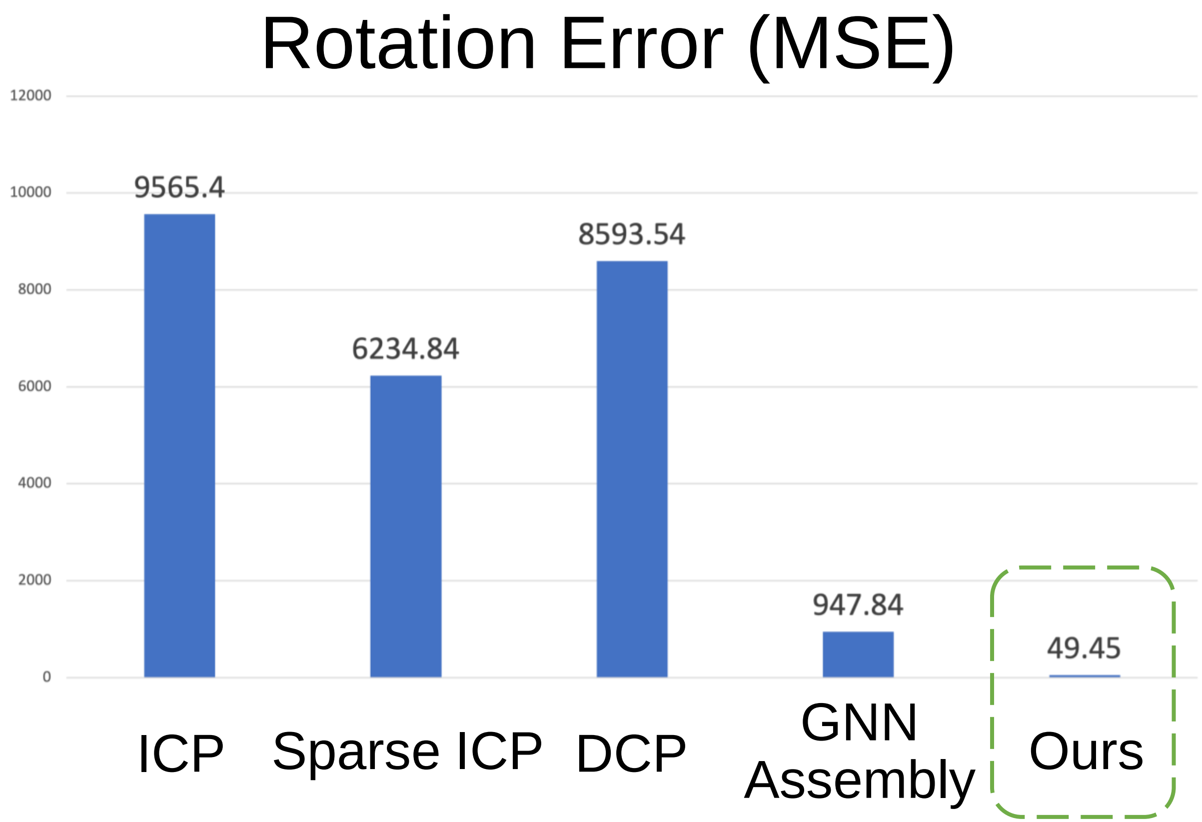
The Geometric Shape Assembly Dataset

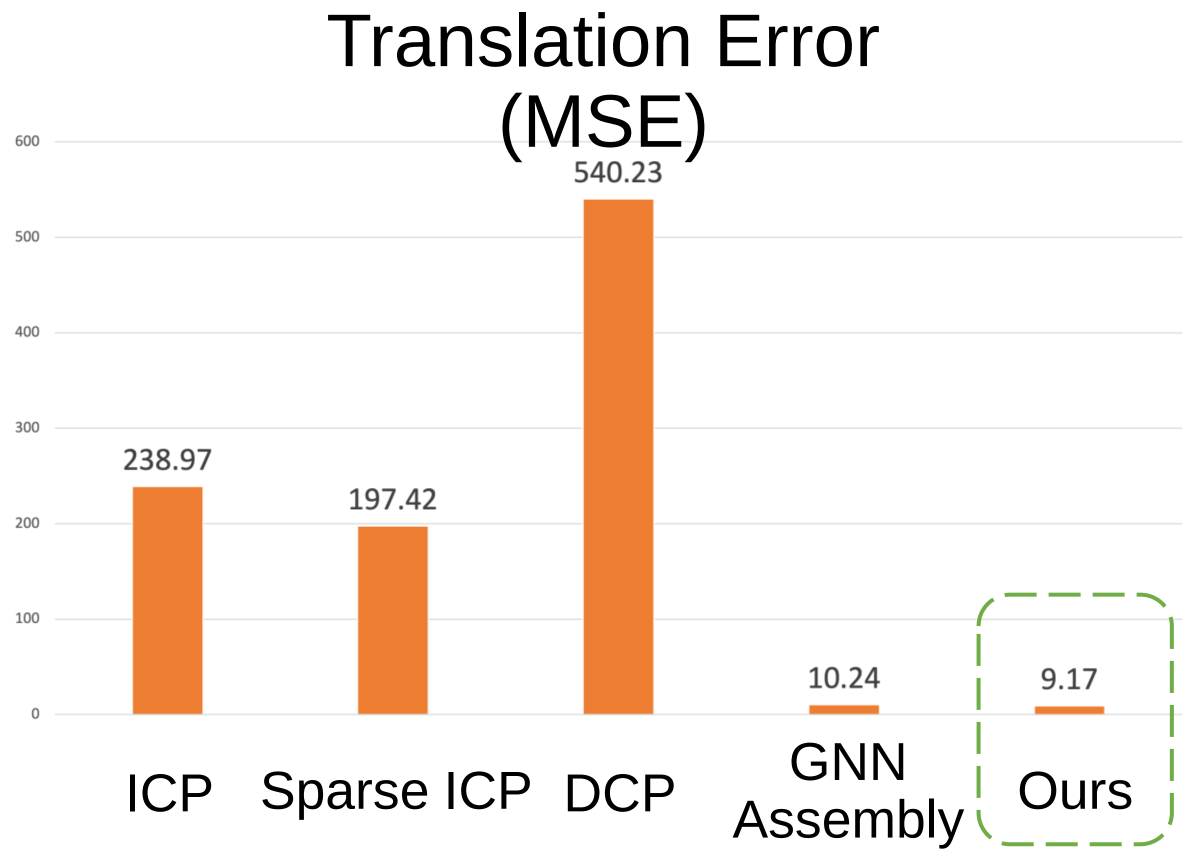


Shell Solid

Object Meshes Different Cut Types Random Poses

Experimental Results





Conclusions

- Formulate the task of pairwise 3D geometric shape assembly

- Propose a self-supervised learning algorithm

- Collect a large-scale geometric shape assembly dataset

- Provide a benchmark with several methods on the proposed tasks

- State-of-the-art results with good generalization