Leveraging SE(3) Equivariance for Learning 3D Geometric Shape Assembly

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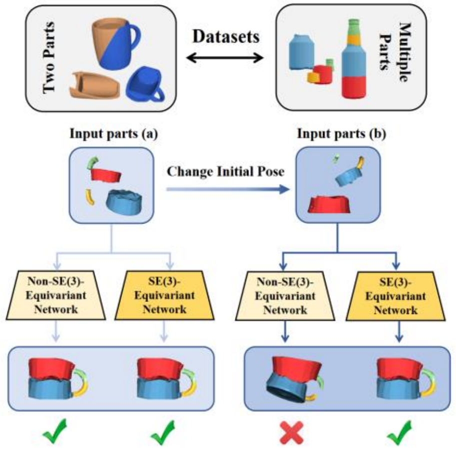
Geometric Shape Assembly

Geometric Shape Assembly aims to assemble different fractured parts into a whole shape. We propose to leverage **SE(3) Equivariance** for learning Geometric Shape Assembly, which disentangles poses and shapes of fractured parts, and performs better than networks without SE(3)-equivariant representations.



SE(3) equivariance & invariance

SE(3), which represents the Special Euclidean Group in three dimensions, characterizes the rigid body motion in 3D space, including 3D translation and rotation.

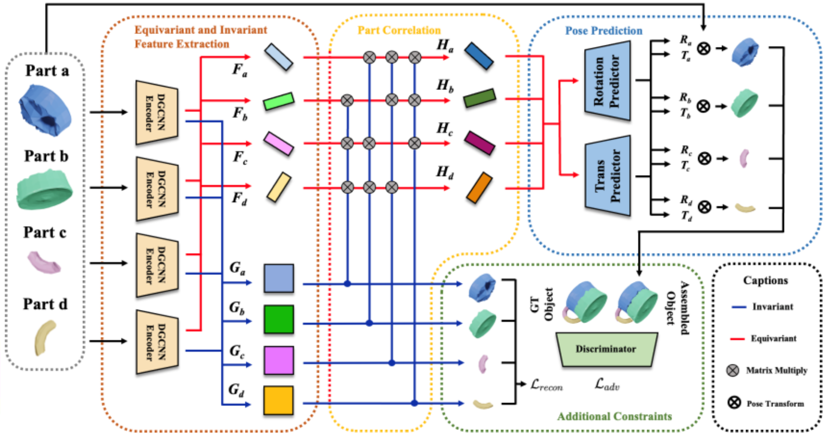
Given an input point cloud $\mathcal{P} \in \mathbb{R}^{n\times 3}$, for any rotation matrix $R \in \mathbb{R}^{3\times 3}$ and translation vector $T \in \mathbb{R}^{3}$. A SE(3) equivariant encoder $\mathcal{E}_{equiv}$ means

$$\mathcal{E}_{equiv}(\mathcal{P}R + T) = \mathcal{E}_{equiv}(\mathcal{P})R + T$$

And a SE(3) invariant encoder $\mathcal{E}_{inv}$ means

$$\mathcal{E}_{inv}(\mathcal{P}R + T) = \mathcal{E}_{inv}(\mathcal{P})$$

Method



Taking as input the point cloud of each part i, our framework first outputs the equivariant representation F_i and invariant representation G_i, computes the correlation between part i and each part j using the matrix multiplication of F_i and G_i, and thus gets each part's equivariant representation H_i with part correlations. H_i is equivariant with input part i, and invariant with input part j

The rotation decoder and the translation decoder respectively take H and decode the rotation and translation of each part. Additional constraints such as adversarial training and canonical point cloud reconstruction using G further improves the performance of our method.

Project Page

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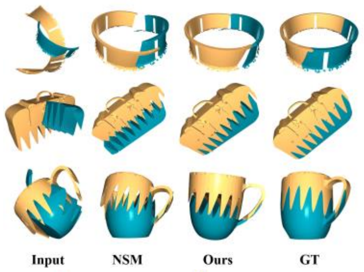
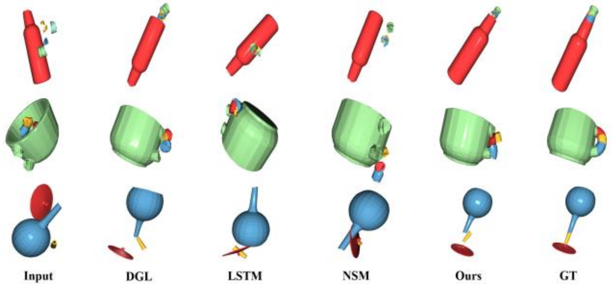
Experiments



We test the performance of out method on two datasets

- Geometric Shape Mating dataset for two-part geometric shape assembly
- Breaking Bad dataset for multi-part geometric shape assembly



We compare our method with SOTA part assembly methods.

Conclusion

We propose to leverage SE(3)-equivariant representations that disentangle shapes and poses to facilitate the task. Our method leverages SE(3) equivariance in part representations considering part correlations, by learning both SE(3)-equivariant and -invariant part representations and aggregating them into SE(3)-equivariant representations. To the best of our knowledge, we are the first to explore leveraging SE(3) equivariance on multiple objects in related fields. Experiments demonstrate the effectiveness of our method.

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