JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

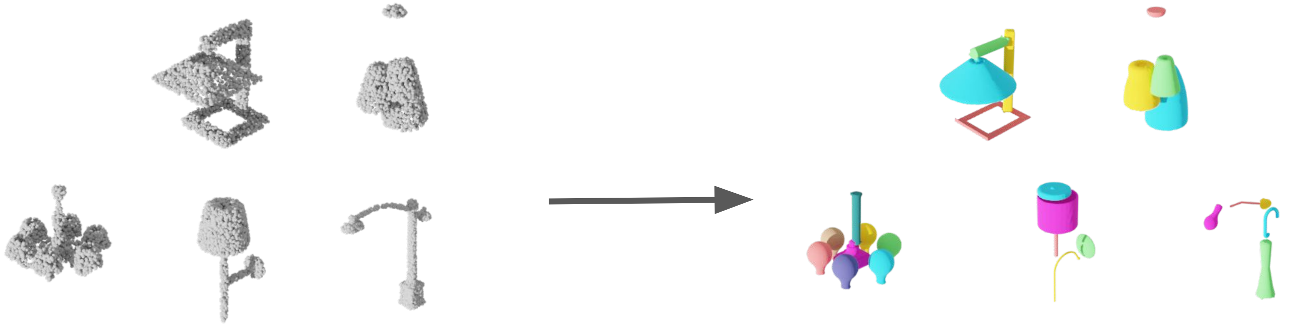
Unsupervised 3D Shape Reconstruction by Part Retrieval and Assembly

Xianghao Xu, Paul Guerrero, Matthew Fisher, Siddhartha Chaudhuri, Daniel Ritchie

Tag: WED-AM-032

Presentation Date: June 21, 2023

Poster Number: 32

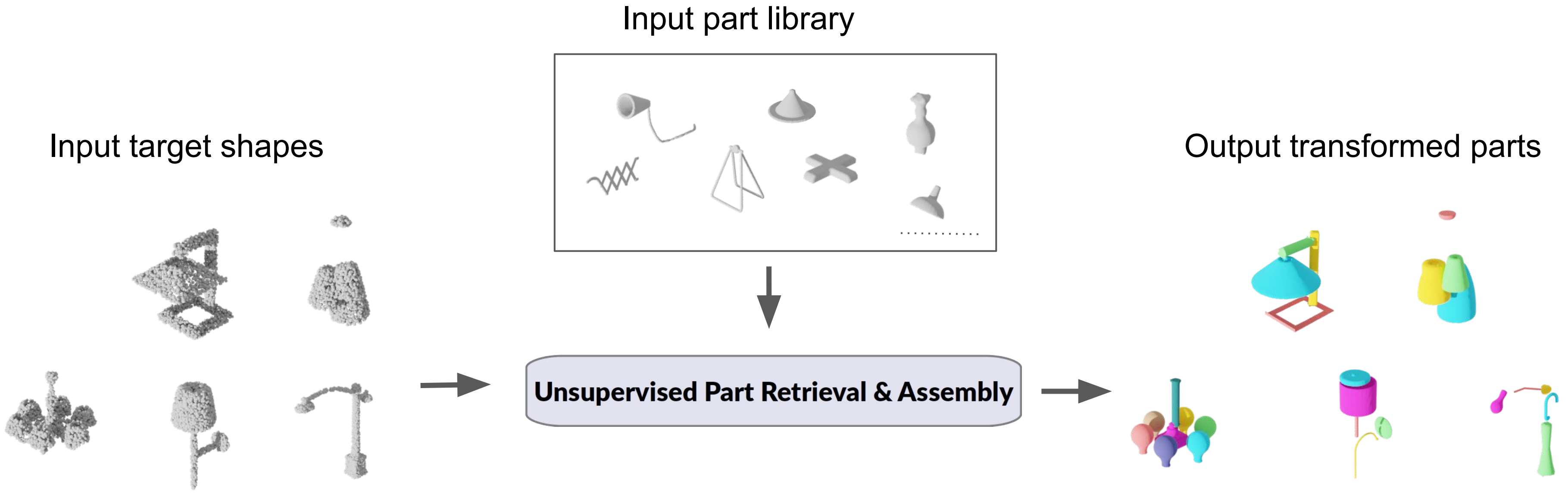


BROWN

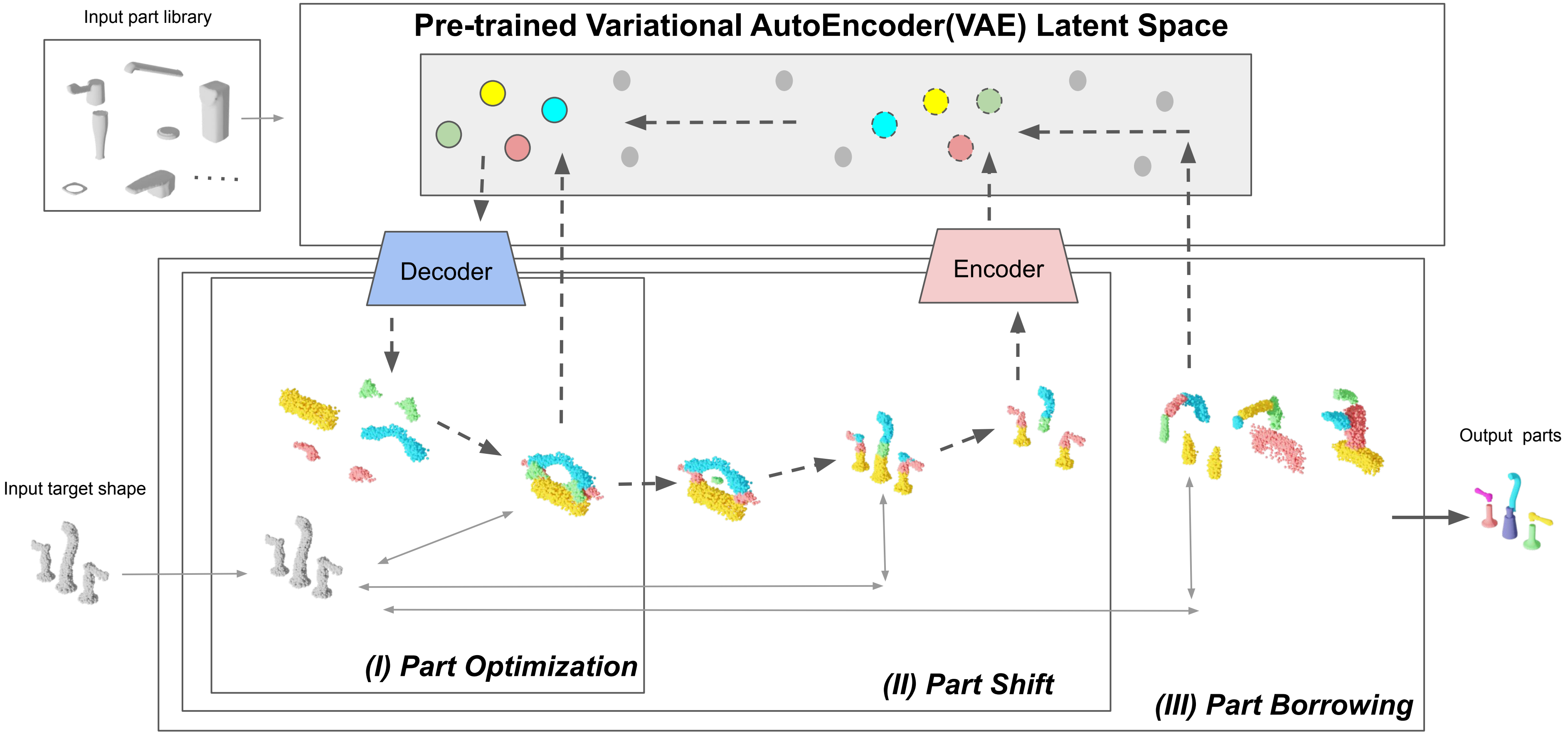
Adobe

Preview

Goal: Representing 3D shapes with parts from a given library of 3D parts

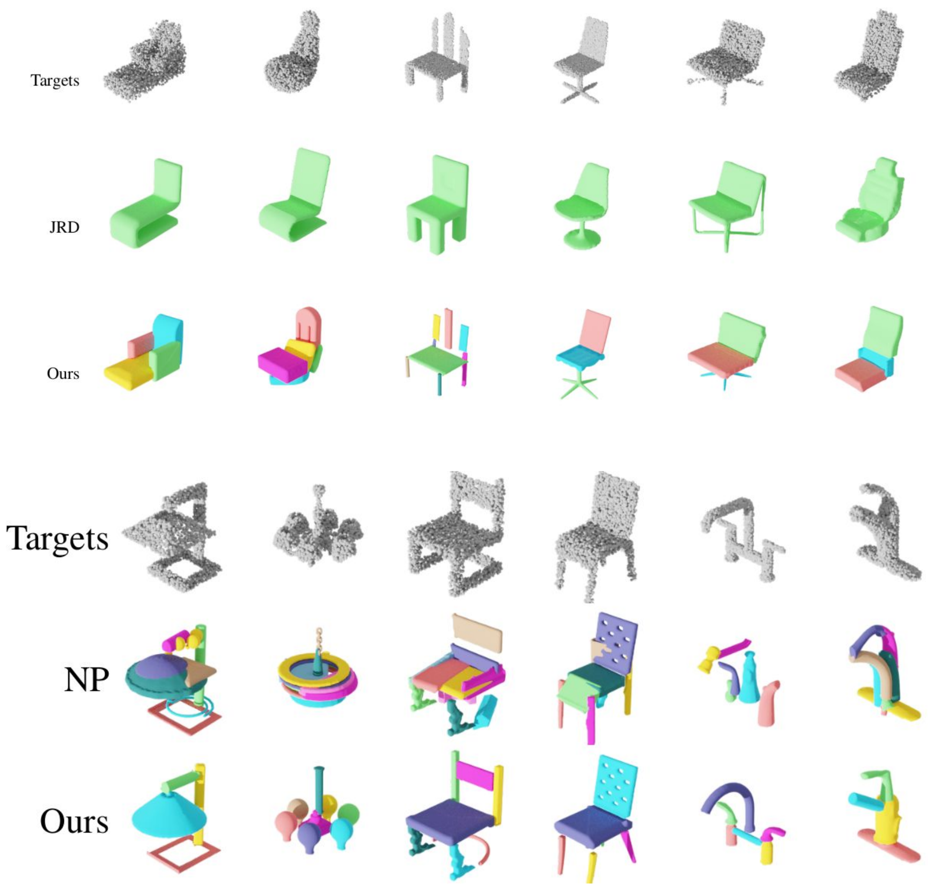


Iterative retrieval and assembly framework



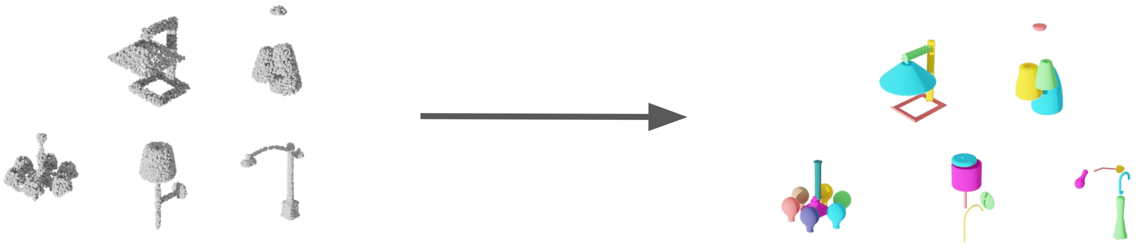
Qualitative results

Our method achieves better reconstruction results

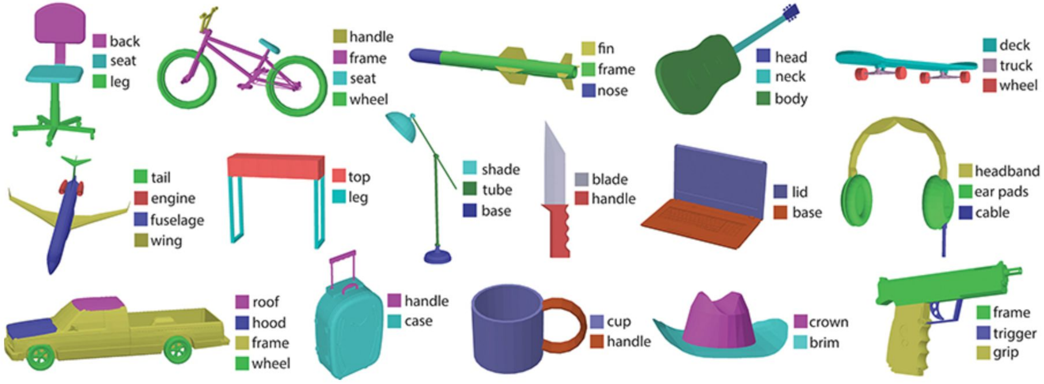


Long version

Motivation: Representing 3D shapes with a set of smaller 3D elements



Aid perception of underlying structure



https://people.cs.umass.edu/~kalo/papers/shapepfcn/

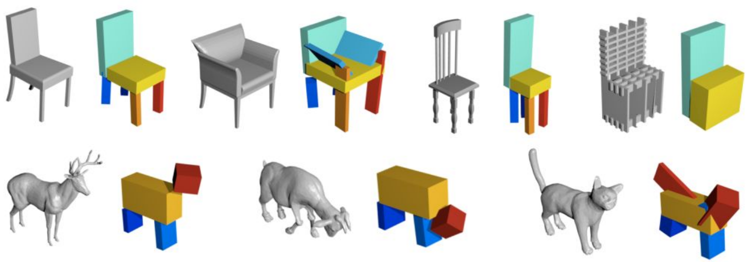
Aid 3D fabrication process

Prior Work : Representing 3D shapes with cuboids

Using of simple parametric primitives leads to coarse approximations

Learning Shape Abstractions by Assembling Volumetric Primitives

Shubham Tulsiani[1], Hao Su[2], Leonidas J. Guibas[2], Alexei A. Efros[1], Jitendra Malik[1]
[1]University of California, Berkeley [2]Stanford University
[1]{shubhtuls, efros, malik}@eecs.berkeley.edu, [2]{haosu, guibas}@cs.stanford.edu



Learning Adaptive Hierarchical Cuboid Abstractions of 3D Shape Collections

CHUN-YU SUN*, Tsinghua University and Microsoft Research Asia
QIAN-FANG ZOU*, University of Science and Technology of China and Microsoft Research Asia
XIN TONG and YANG LIU†, Microsoft Research Asia

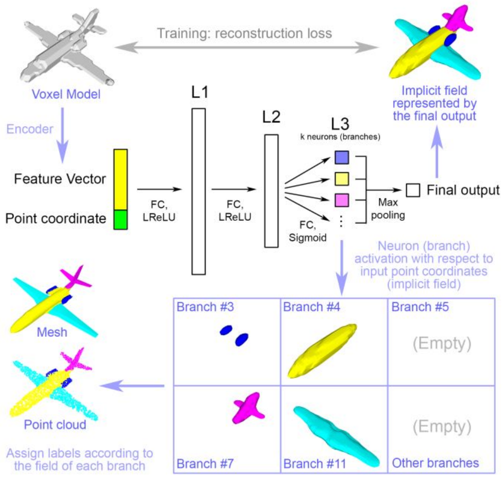
Prior Work : Representing 3D shapes with learned primitives

Offers too little control over the decomposition

BAE-NET: Branched Autoencoder for Shape Co-Segmentation

Zhiqin Chen[1], Kangxue Yin[1], Matthew Fisher[2], Siddhartha Chaudhuri[2,3], and Hao Zhang[1]

[1]Simon Fraser University [2]Adobe Research [3]IIT Bombay



Neural Parts: Learning Expressive 3D Shape Abstractions with Invertible Neural Networks

Despoina Paschalidou[1,5,6] Angelos Katharopoulos[3,4] Andreas Geiger[1,2,5] Sanja Fidler[6,7,8]

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[3]Idiap Research Institute, Switzerland [4]École Polytechique Fédérale de Lausanne (EPFL)

[5]Max Planck ETH Center for Learning Systems [6]NVIDIA [7]University of Toronto [8]Vector Institute

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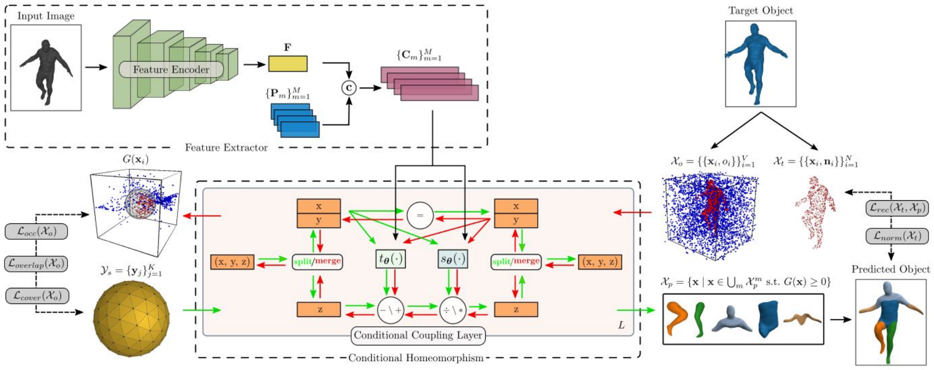
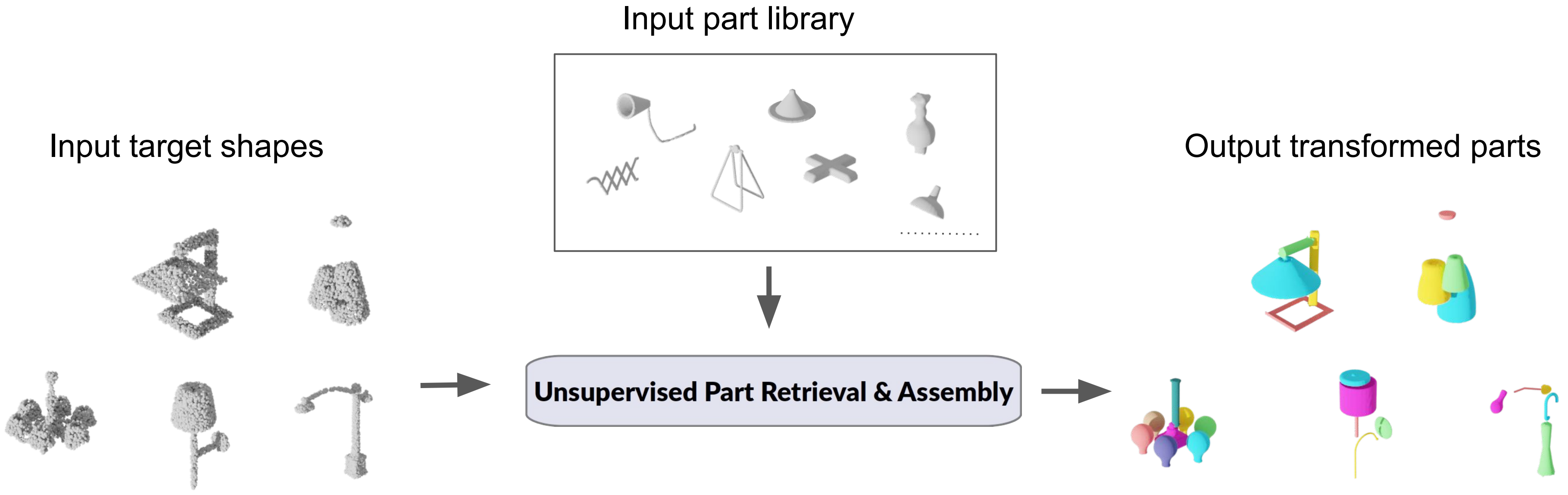
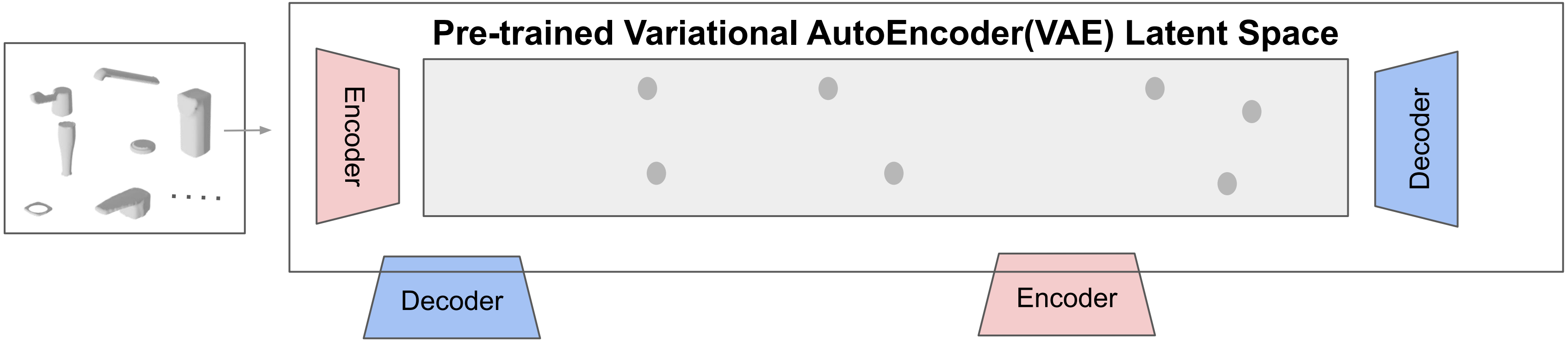
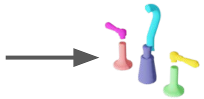


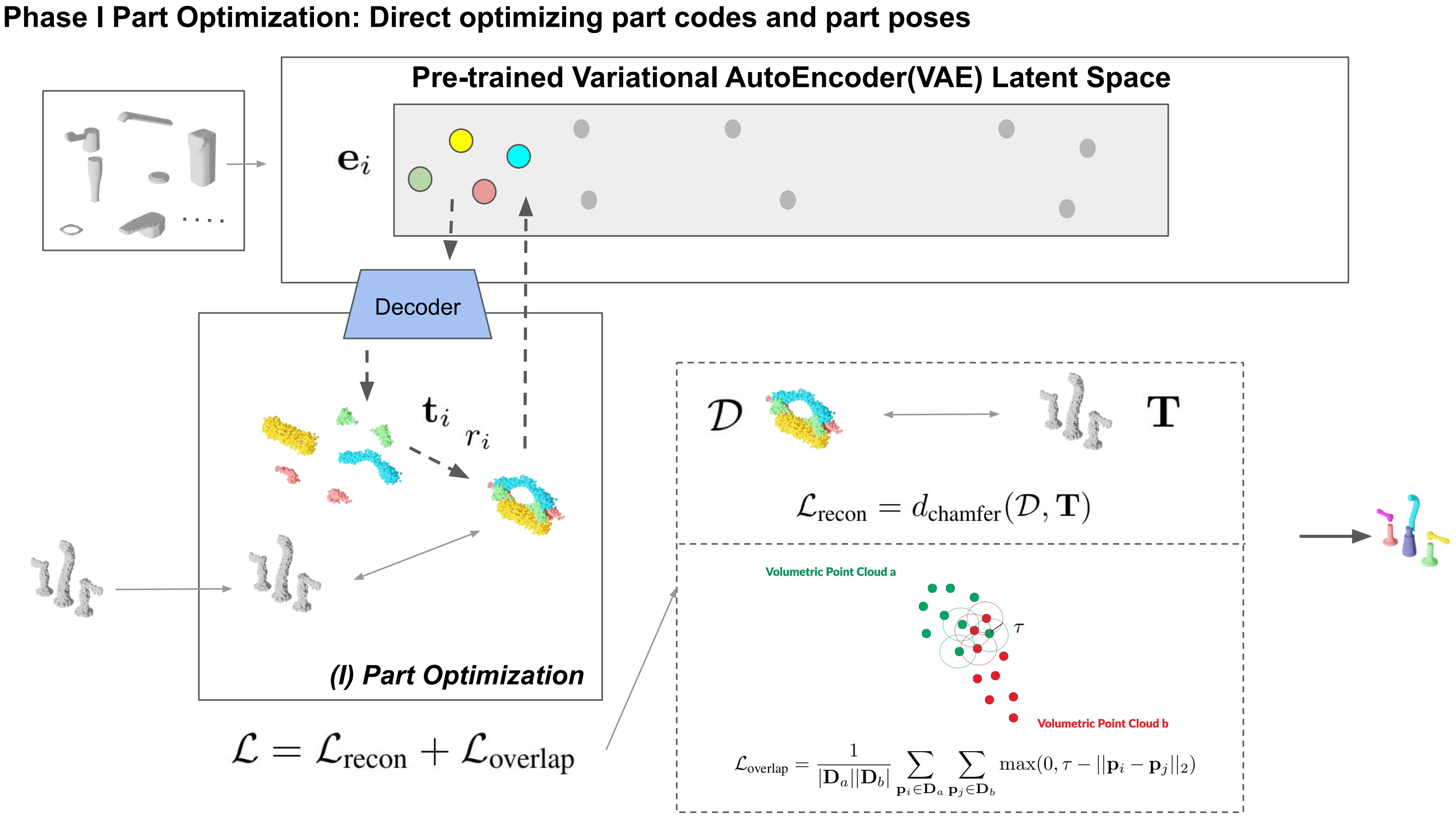
Goal: Representing 3D shapes with a library of 3D parts



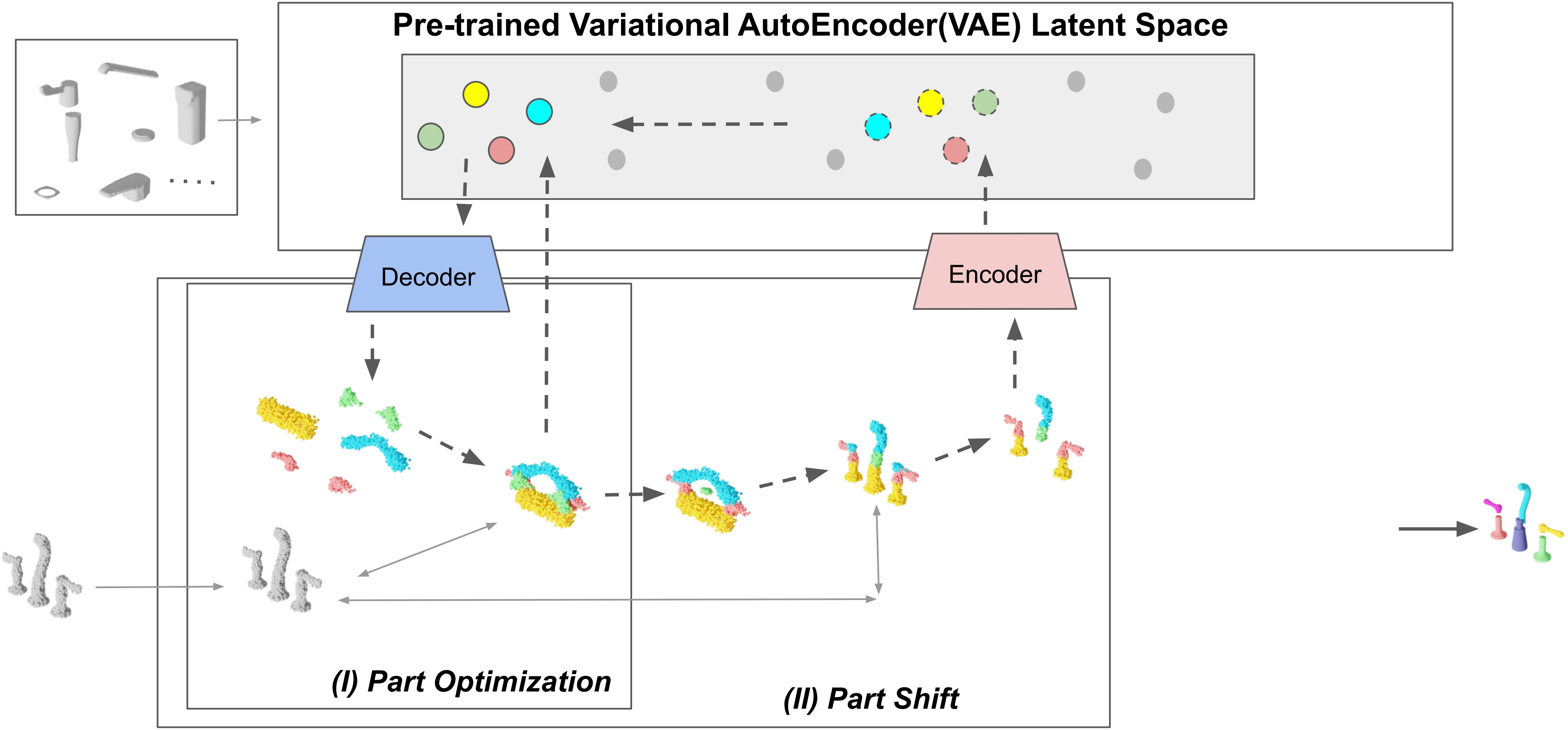
A pre-trained latent space to turn the discrete into continuous



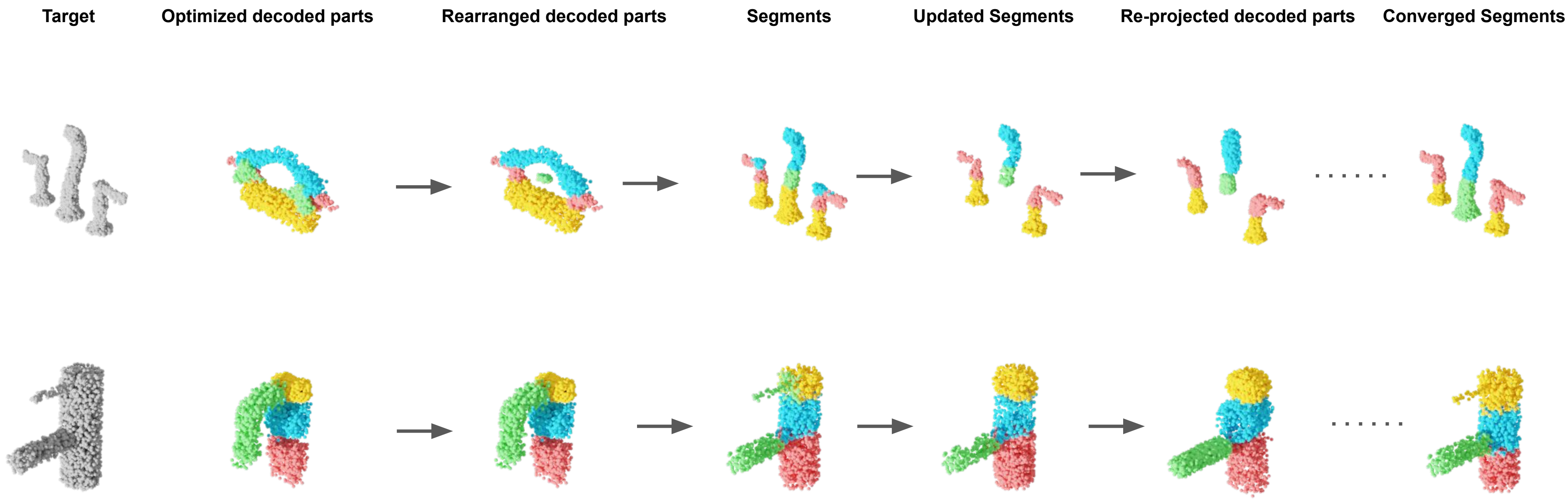



Phase I Part Optimization: Direct optimizing part codes and part poses
Pre-trained Variational AutoEncoder(VAE) Latent Space
$\mathbf{e}_i$
Decoder
$\mathbf{t}_i$
r_i
(I) Part Optimization
$\mathcal{L} = \mathcal{L}_{\text{recon}} + \mathcal{L}_{\text{overlap}}$
$\mathcal{D}$
$\mathbf{T}$
$\mathcal{L}_{\text{recon}} = d_{\text{chamfer}}(\mathcal{D}, \mathbf{T})$
Volumetric Point Cloud a
τ
Volumetric Point Cloud b
$\mathcal{L}_{\text{overlap}} = \frac{1}{|\mathbf{D}_a||\mathbf{D}_b|} \sum_{\mathbf{p}_i \in \mathbf{D}_a} \sum_{\mathbf{p}_j \in \mathbf{D}_b} \max(0, \tau - ||\mathbf{p}_i - \mathbf{p}_j||_2)$

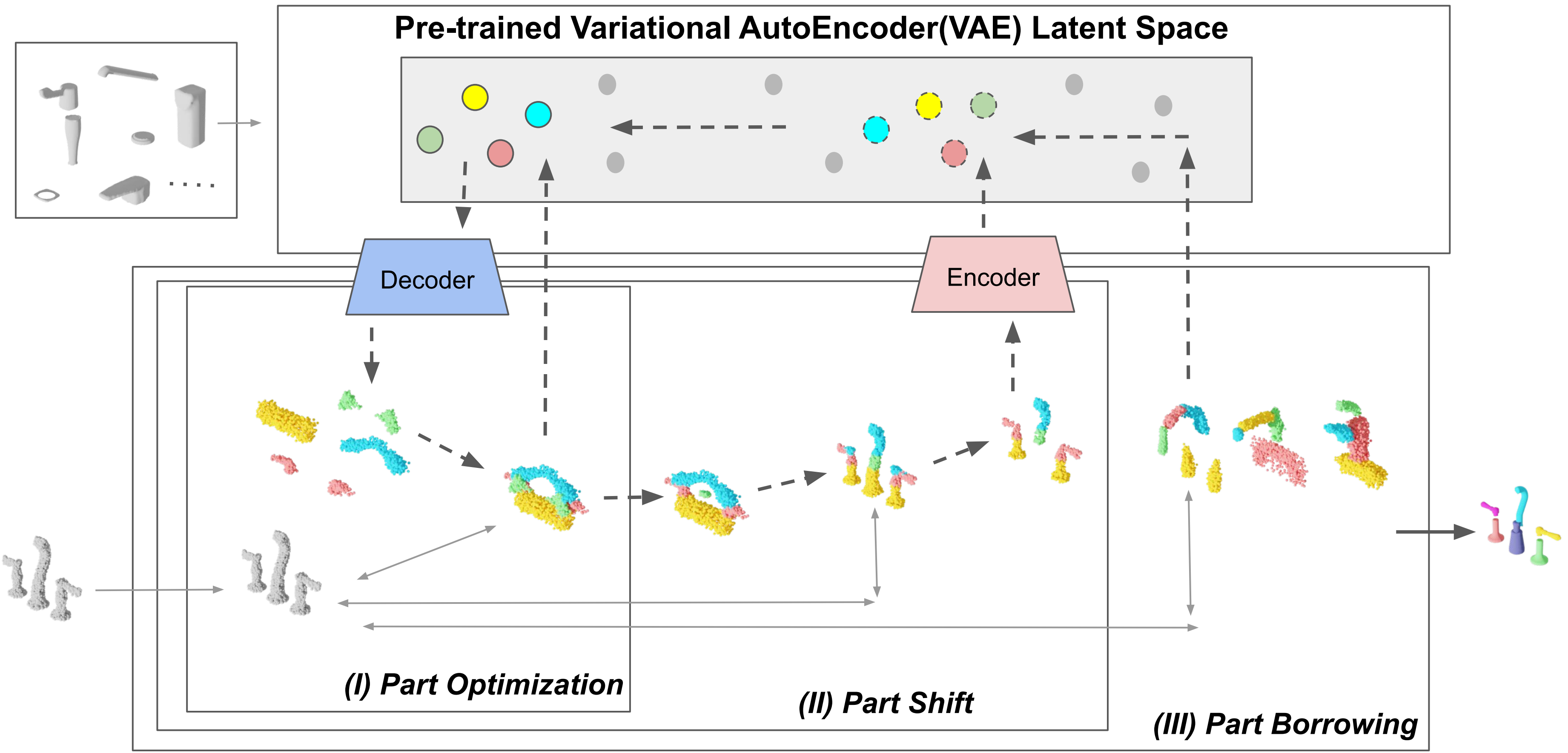
Phase II Part Shift: segmenting the target and re-projecting the segments to escape local optima



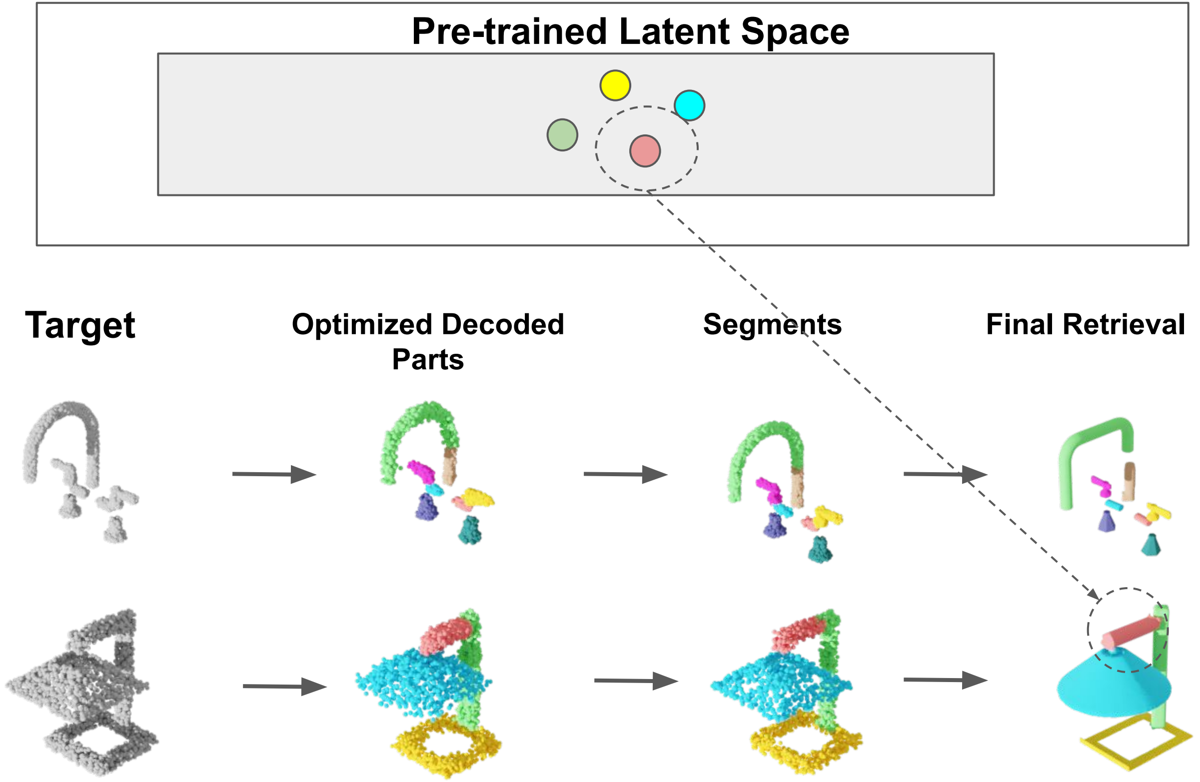
Part Shift: A sequence of segment refining operations



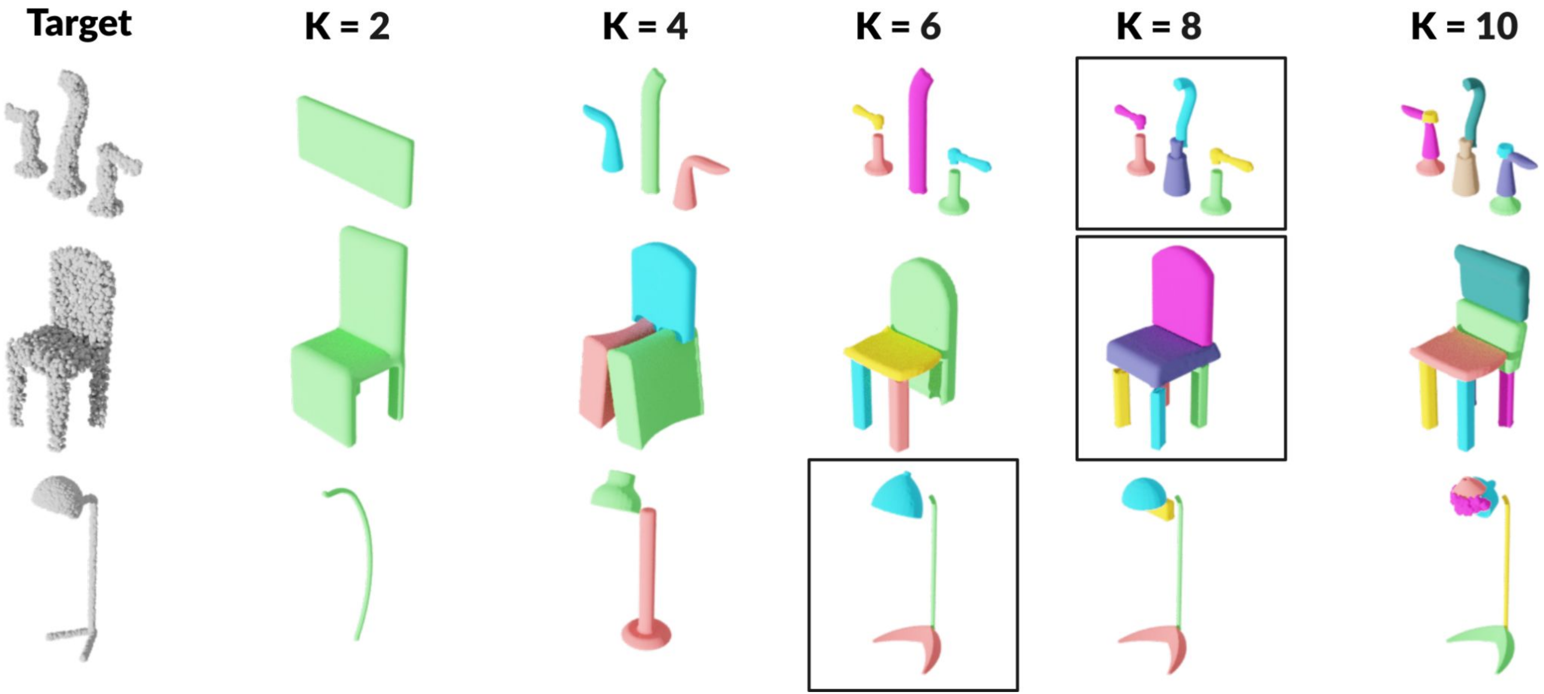
Part Borrowing: borrowing good part decompositions from other shapes



Retrieving parts based on segmentation



Choosing number of parts



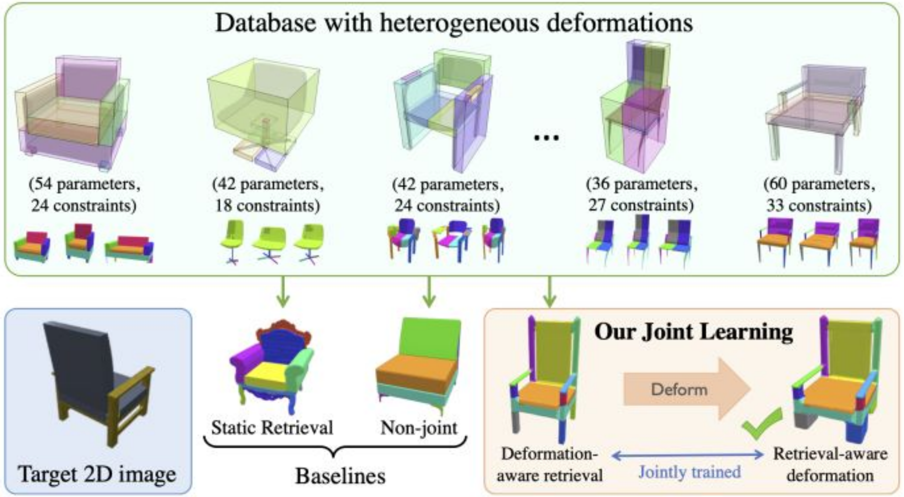
$$d_{\text{chamfer}}((\mathcal{P}^k), \mathbf{T}) + \alpha|(\mathcal{P}^k)|$$

Let’s see some results

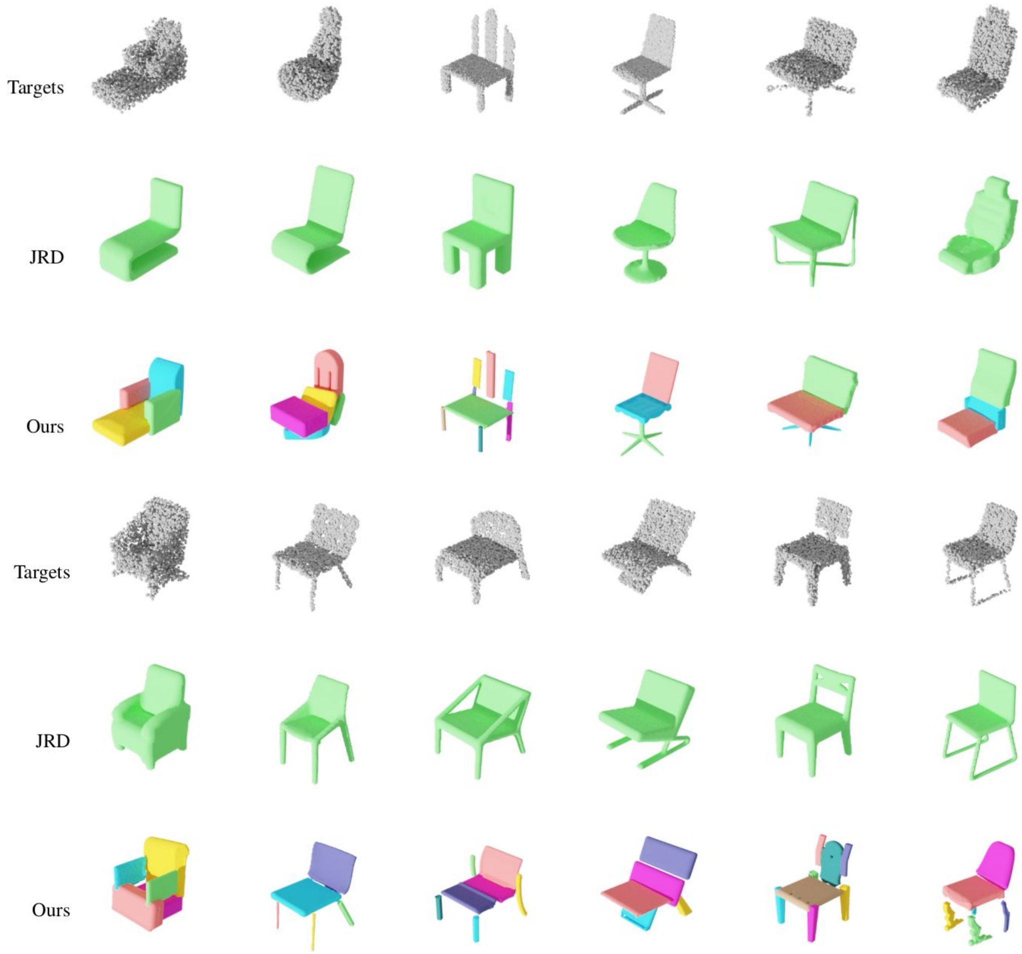
Experiment 1: Comparison to JRD

Joint Learning of 3D Shape Retrieval and Deformation

Mikaela Angelina Uy[1] Vladimir G. Kim[2] Minhyuk Sung[3] Noam Aigerman[2]
Siddhartha Chaudhuri[2,4] Leonidas Guibas[1]
[1]Stanford University [2]Adobe Research [3]KAIST [4]IIT Bombay



Our method handles the structure difference between source shapes and target shapes



Experiment 2: Comparison to Neural Parts(NP)

Neural Parts: Learning Expressive 3D Shape Abstractions with Invertible Neural Networks

Despoina Paschalidou[1,5,6] Angelos Katharopoulos[3,4] Andreas Geiger[1,2,5] Sanja Fidler[6,7,8]
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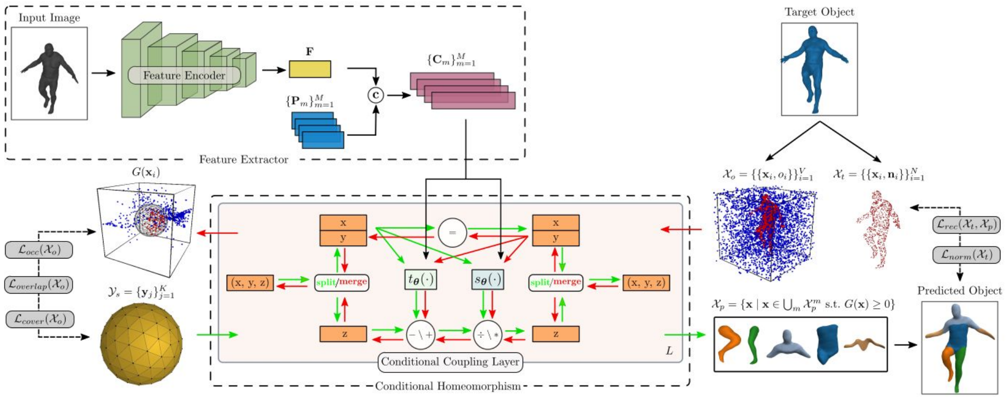
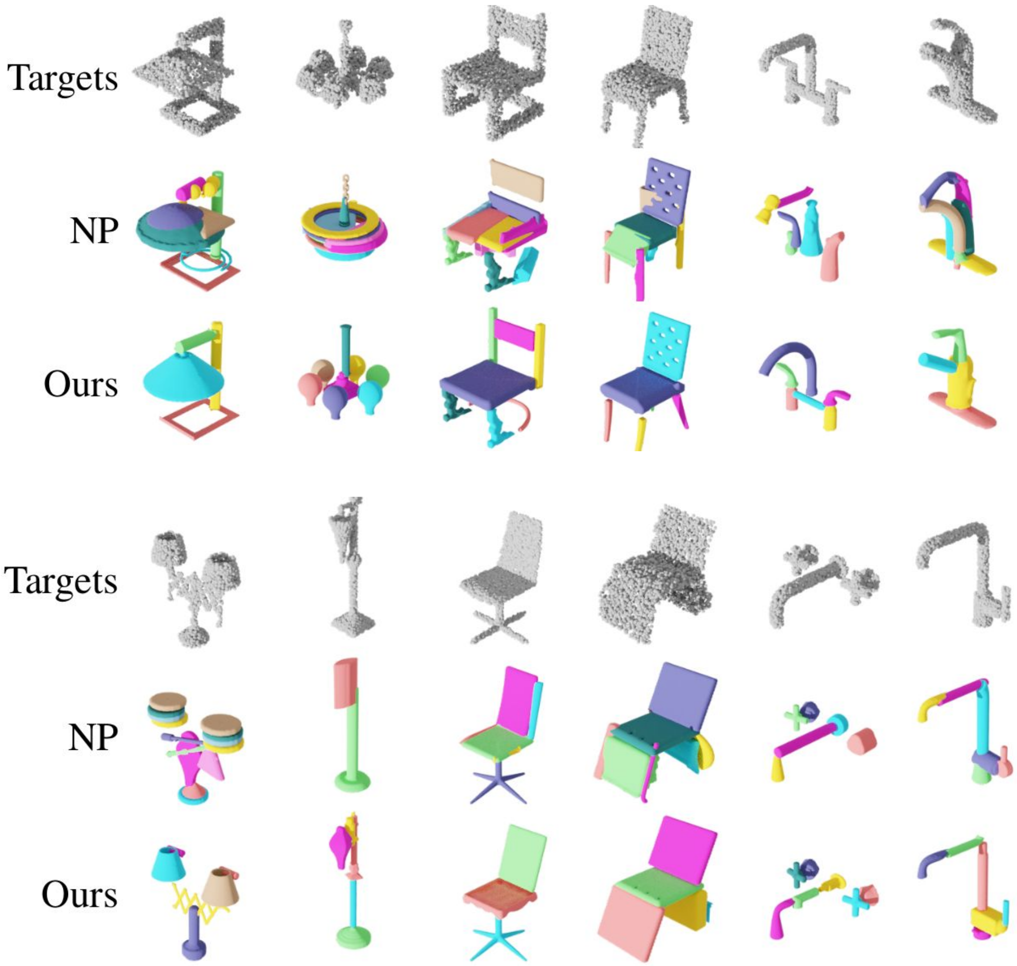
{firstname.lastname}@tue.mpg.de angelos.katharopoulos@idiap.ch sfidler@nvidia.com



Our part aware method generates cleaner and better results



Our method outperforms both baselines in all metrics across all categories

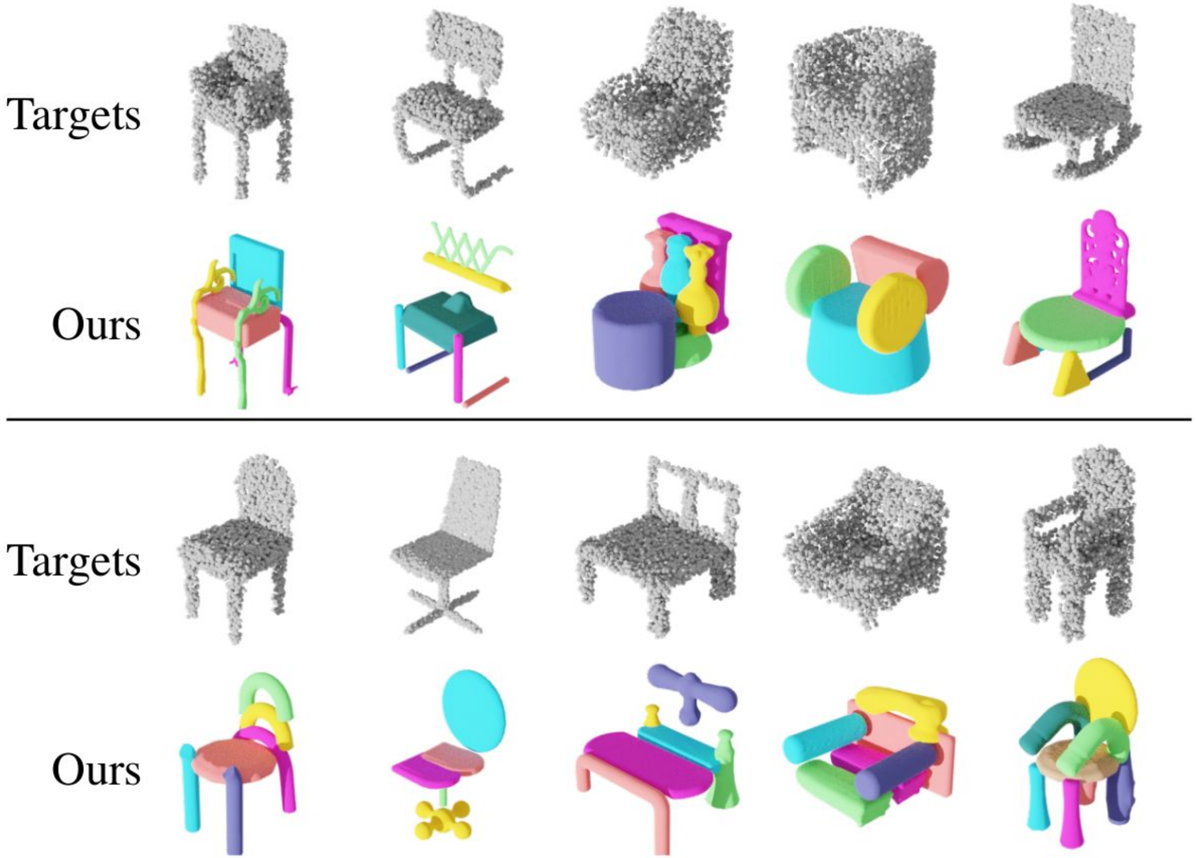
SCD: Surface Points Chamfer Distance
VCD: Volumetric Points Chamfer Distance

Category	Method	Train (SCD) ↓	Train (VCD) ↓	Test (SCD) ↓	Test (VCD) ↓
Lamp	NP	0.349	0.204	0.390	0.195
	Ours	**0.307**	**0.163**	**0.303**	**0.163**
Faucet	NP	0.326	0.171	0.370	0.174
	Ours	**0.256**	**0.135**	**0.288**	**0.134**
Chair	JRD	0.746	0.448	0.669	0.397
	NP	0.495	0.233	0.547	0.240
	Ours	**0.470**	**0.219**	**0.539**	**0.234**
Average	JRD	0.746	0.448	0.669	0.397
	NP	0.390	0.203	0.436	0.203
	Ours	**0.344**	**0.172**	**0.377**	**0.177**

Cross-category reconstructions

With Lamp Parts :

With Faucet Parts :



Conclusion

Contribution:

- An unsupervised algorithm which retrieves and places 3D parts from a given part library to reconstruct 3D target shapes.
  – Turns combinatorial problem into a semi-continuous optimization problem
  – Introduces a multi-phase framework to avoid the worst of local optimas

Future Work:

- Introducing physical priors into the optimization to make reconstructions more physically plausible

- Supporting incomplete point clouds as input.

Thank you for your time !