



Can 3D Generative Models Help 3D Assembly?

ICML 2026

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Julia Galway-Witham, Xue Wang, Scott A. Williams, Radu Iovita,
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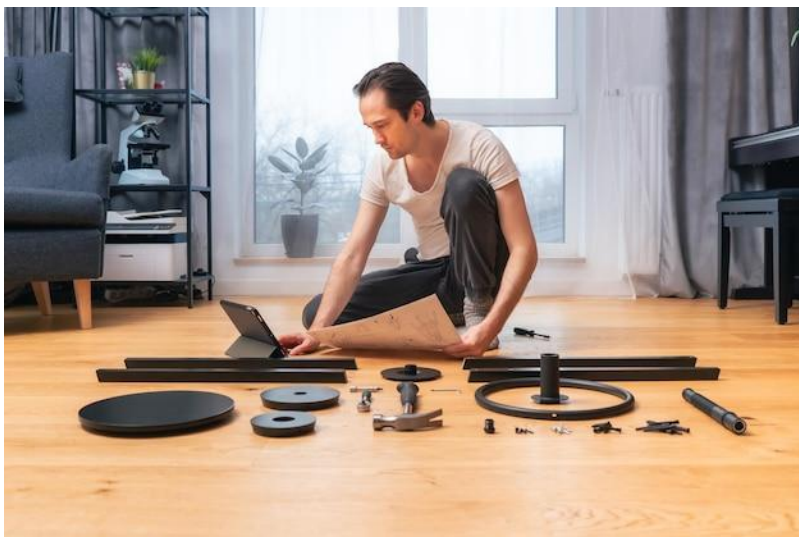
3D Assembly



Fossil



LEGO Toy

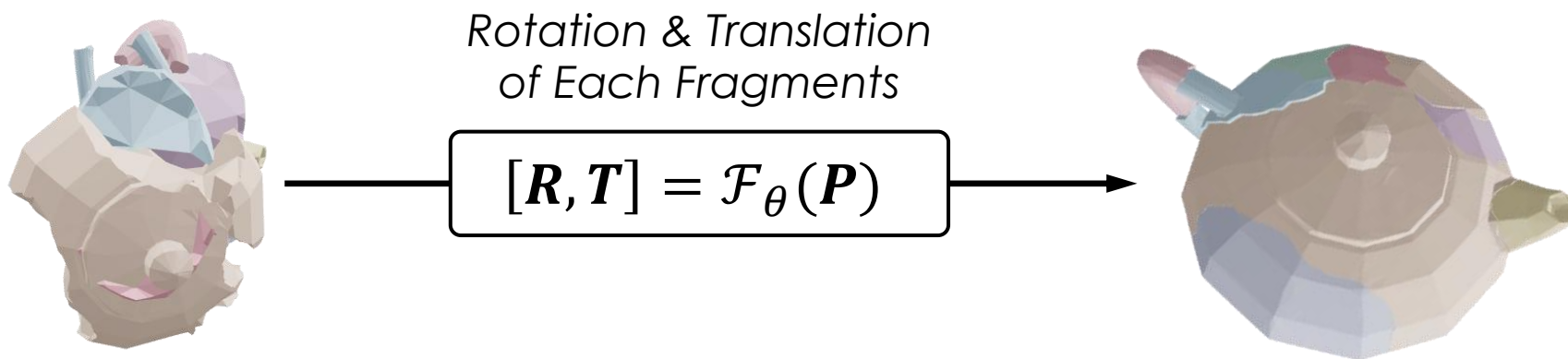


IKEA
Furniture



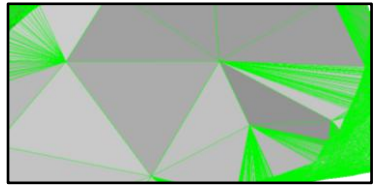
Broken
Item

3D Assembly

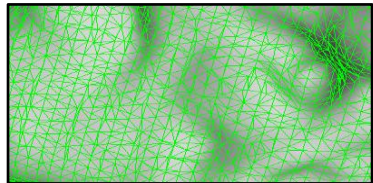


3D Assembly: Path to Physical Spatial Intelligence

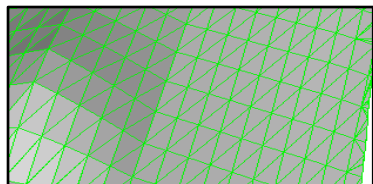
Diverse Local Feature



Physical Simulated



Real World Scan



Geometric Simulation

Diverse Object



PartNext¹



Bone, Ceramics, Lithics

Diverse Scale



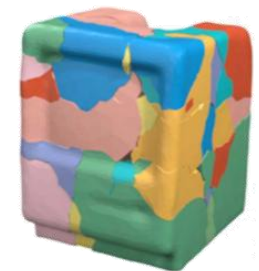
$N = 69$



$N = 41$



$N = 49$



$N = 45$

1. Wang, Penghao, et al. "Partnext: A next-generation dataset for fine-grained and hierarchical 3d part understanding." NeurIPS(2025).

Previous

*PuzzleFusion++
(ICLR25)*



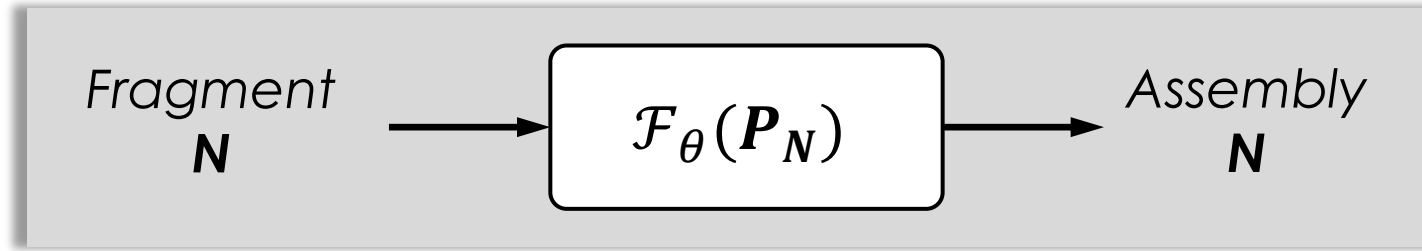
*GARF
(ICCV25)*



*RPF
(NeurIPS25)*

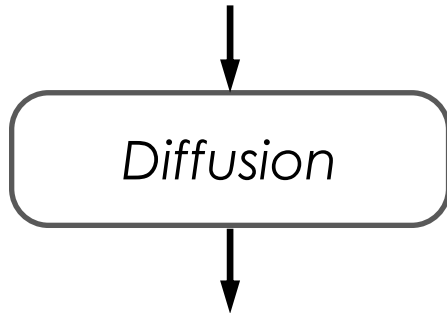


Previous



PuzzleFusion++
(ICLR25)

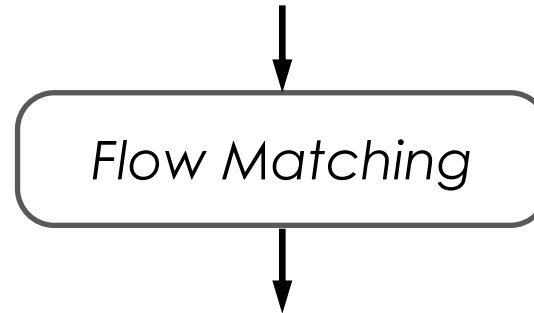
Noise $\in \mathcal{N}(\mu, \sigma^2)$



Pose $\in \mathbb{R}^7$

GARF
(ICCV25)

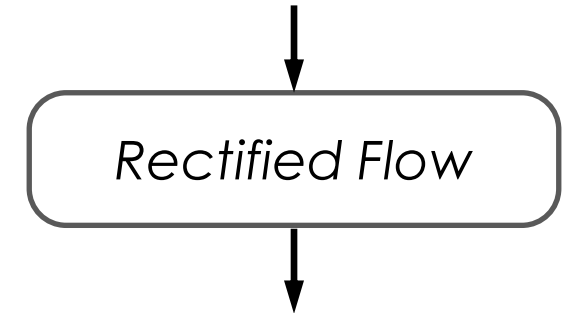
Noise $\in \mathcal{N}(\mu, \sigma^2)$



Pose $\in \mathbb{R}^7$

RPF
(NeurIPS25)

Noise $\in \mathcal{N}(\mu, \sigma^2)$



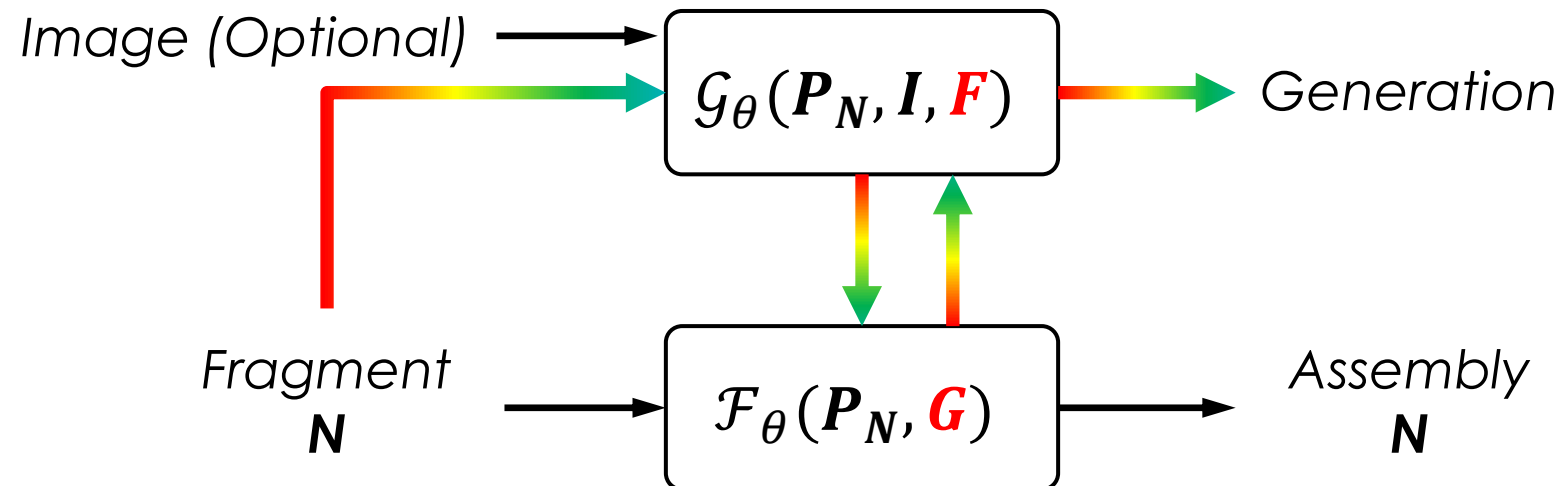
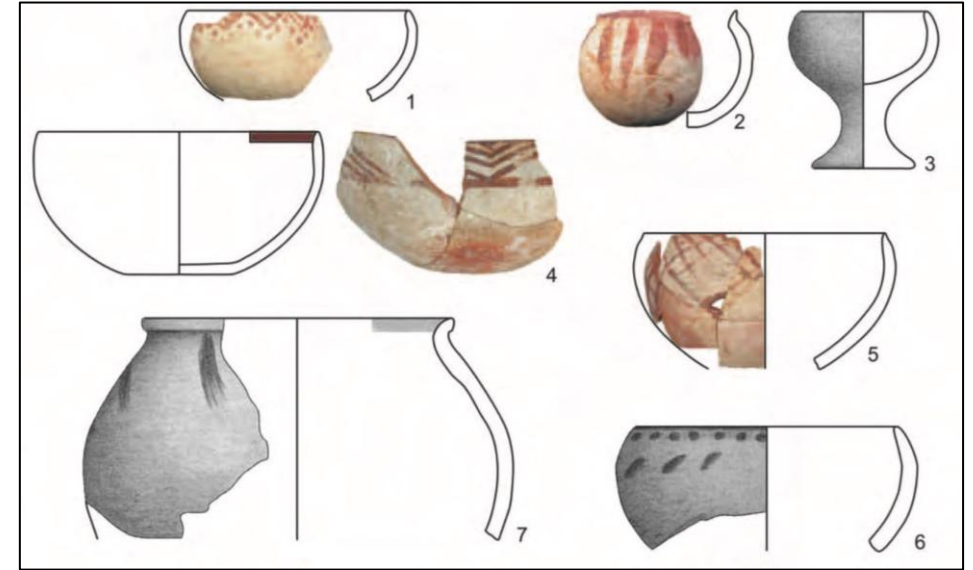
Point Clouds $\in \mathbb{R}^{n \times 3}$

↓ SVD

Pose $\in \mathbb{R}^7$

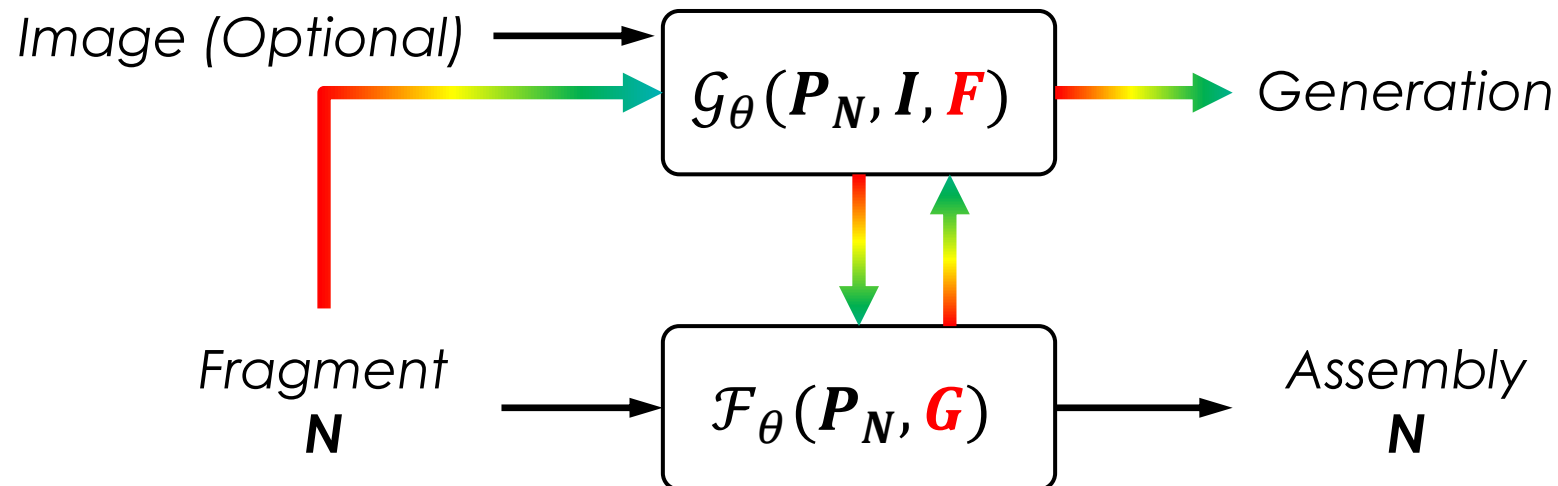
However

- There are always **missing parts**: conservators often infer absent regions from the available fragments and perform gap-filling to restore a plausible, complete form.

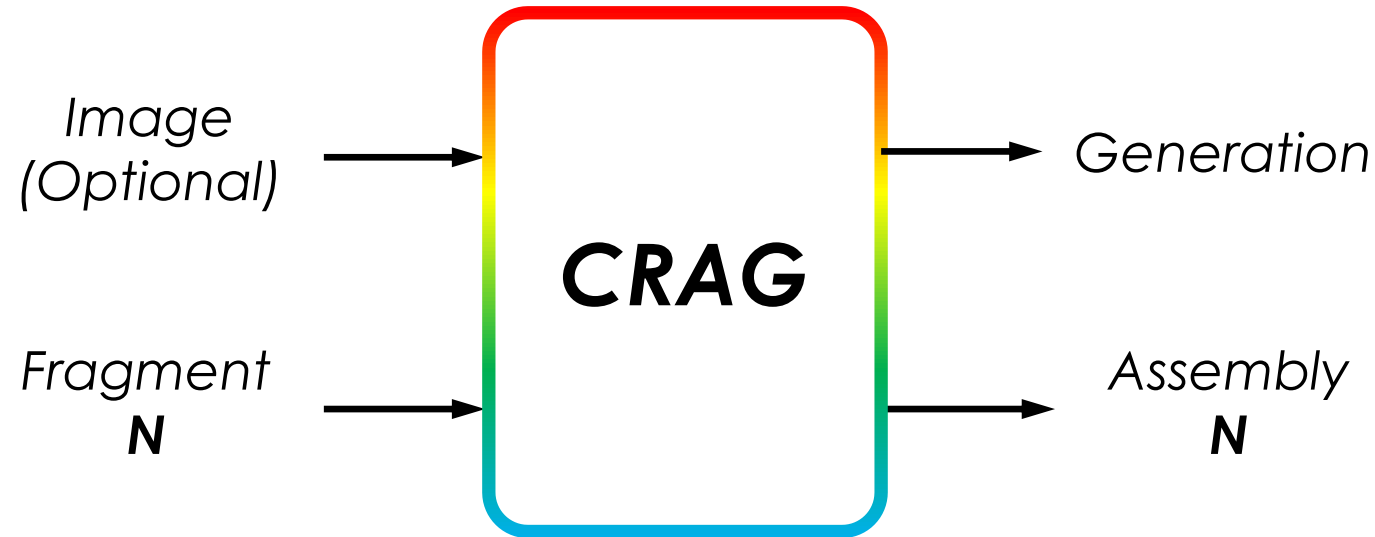


Could 3D assembly and generation be unified?

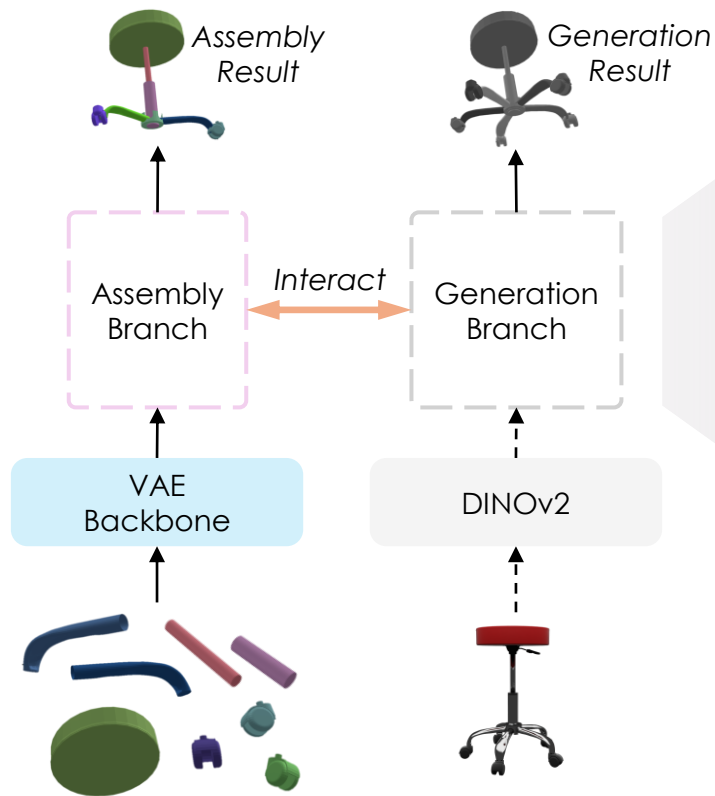
- Challenge 1: How to **infer the global shape** across diverse object categories.
- Challenge 2: a **shared latent space** that can embed an unordered set of variable-size, partial, and noisy fragments into a representation for both assembly and generation
- Challenge 3: effective **bidirectional information exchange**



Could 3D assembly and generation be unified?



Challenge 1: Infer the Global Shape



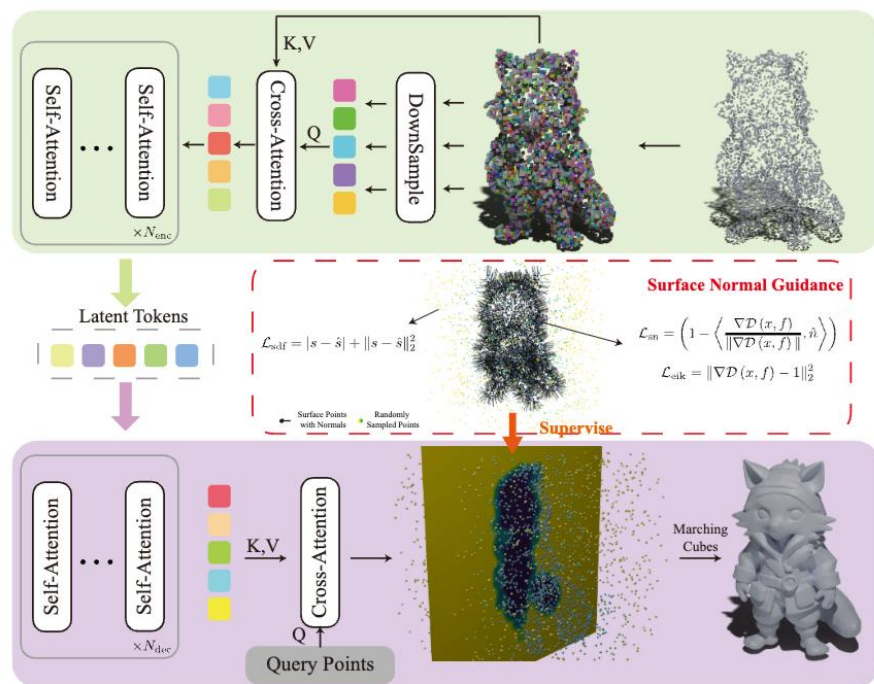
(a) Coupled Architecture



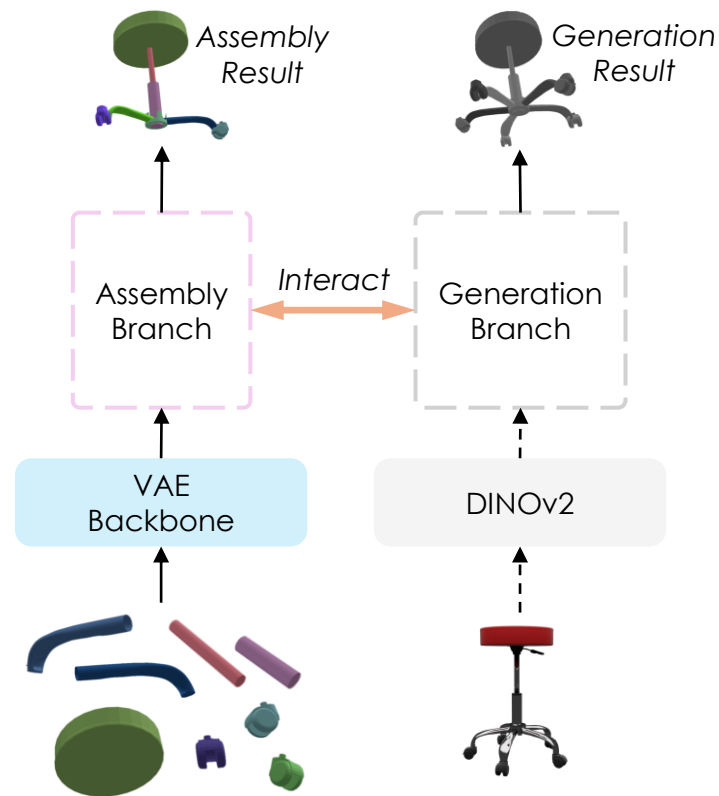
3M Large-scale Object Dataset

Pretrained TripoSG Model

Challenge 2: Shared Latent Space

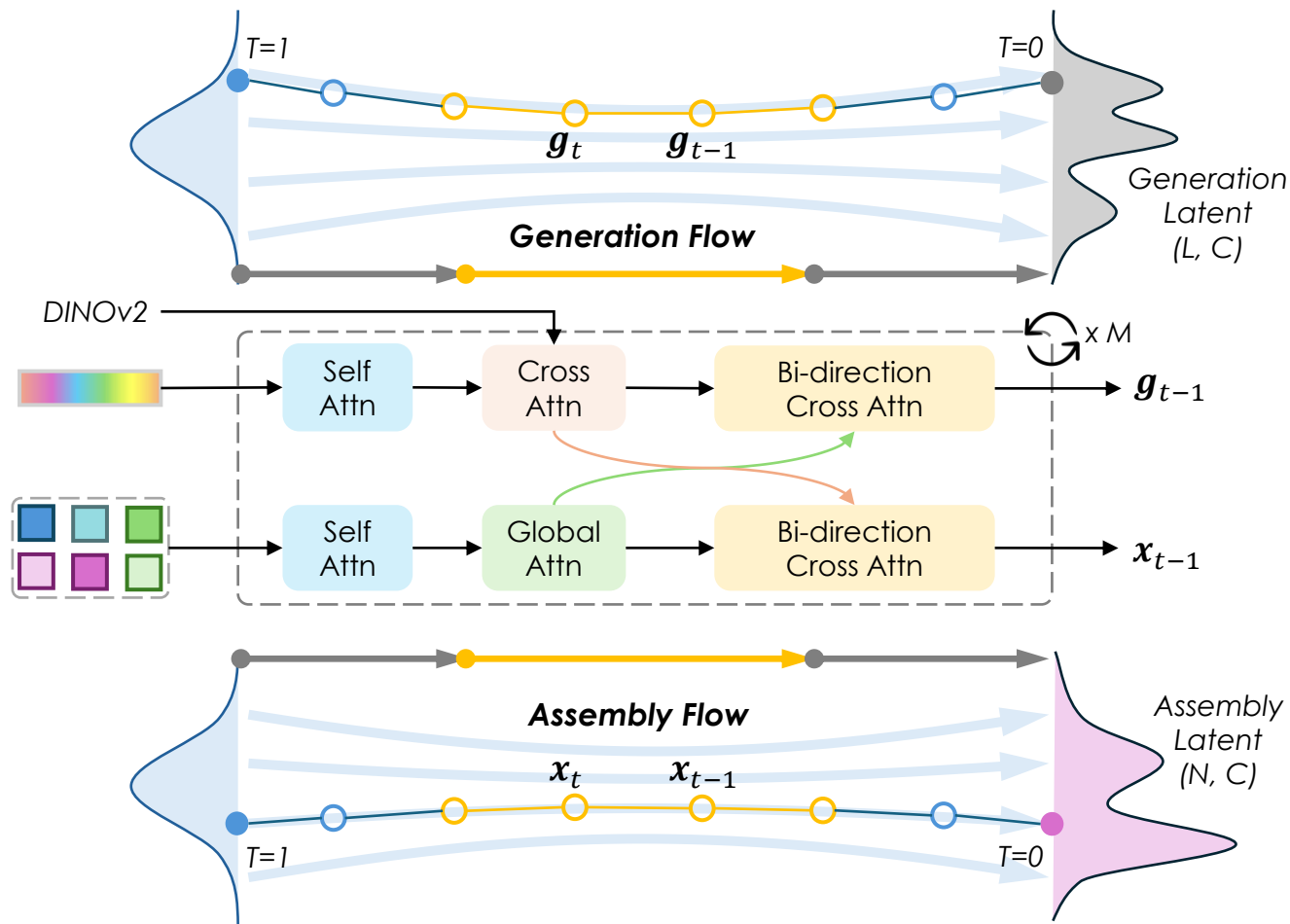


Shared VAE for Fragment Embedding



(a) Coupled Architecture

Challenge 3: Bidirectional Information Exchange



Bi-direction Cross Attention

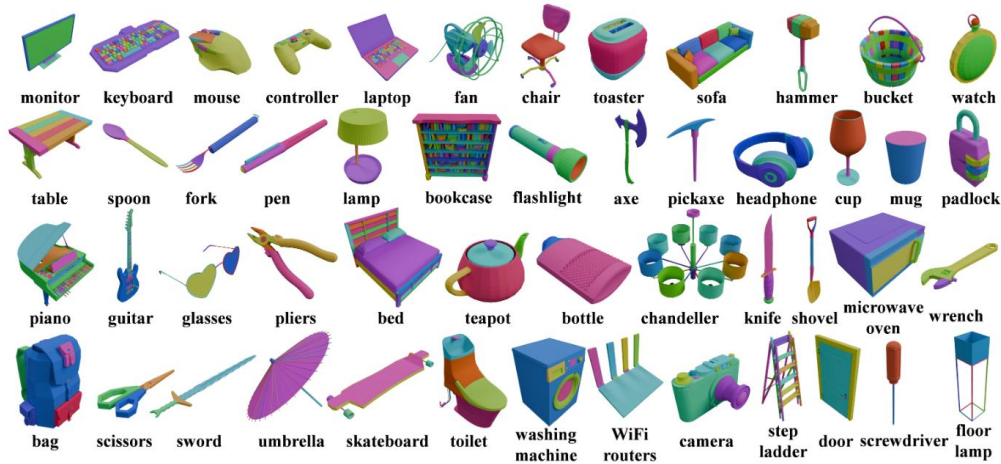
$$h_{\text{gen}}^{(\ell)} = h_{\text{gen}}^{(\ell)} + \text{CrossAttn}(h_{\text{gen}}^{(\ell)}, h_{\text{asm}}^{(\ell)}),$$

$$h_{\text{asm}}^{(\ell)} = h_{\text{asm}}^{(\ell)} + \text{CrossAttn}(h_{\text{asm}}^{(\ell)}, h_{\text{gen}}^{(\ell)}),$$

(b) Iteration with Joint Flow

Dataset

Part-level Assembly PartNext¹



Training set: 15563
Evaluation set: 3903

Fracture Assembly Breaking Bad²



Training set: 7872
Evaluation set: 3697

Fracture Assembly Morphosource³



Training set: 1744
Evaluation set: 437

1. Wang, Penghao, et al. "Partnext: A next-generation dataset for fine-grained and hierarchical 3d part understanding." *NeurIPS*(2025).
2. Sellán, Silvia, et al. "Breaking bad: A dataset for geometric fracture and reassembly." *NeurIPS*(2022).
3. Boyer, Doug M., et al. "Morphosource: archiving and sharing 3-D digital specimen data." *The Paleontological Society Papers* 22 (2016): 157-181.

Experiment

Does generation improve assembly by providing a holistic prior?

Can we still assemble the observed parts and synthesize a complete object from incomplete fragment sets?

Does part-level evidence help disambiguate image conditioned 3D generation?

Does generation improve assembly by providing a holistic prior?

RE: Rotation Error

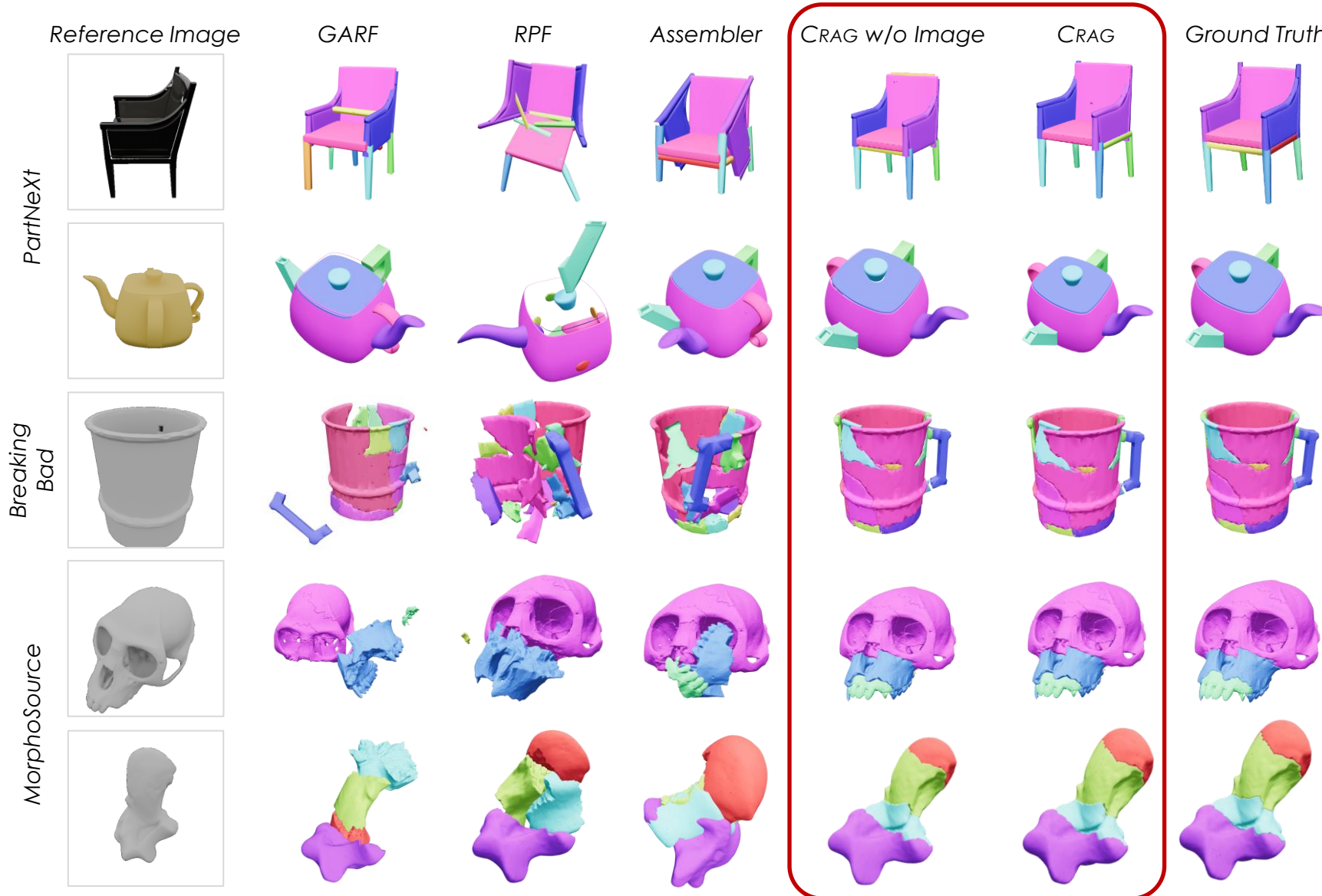
TE: Translation Error

PA: Part Accuracy

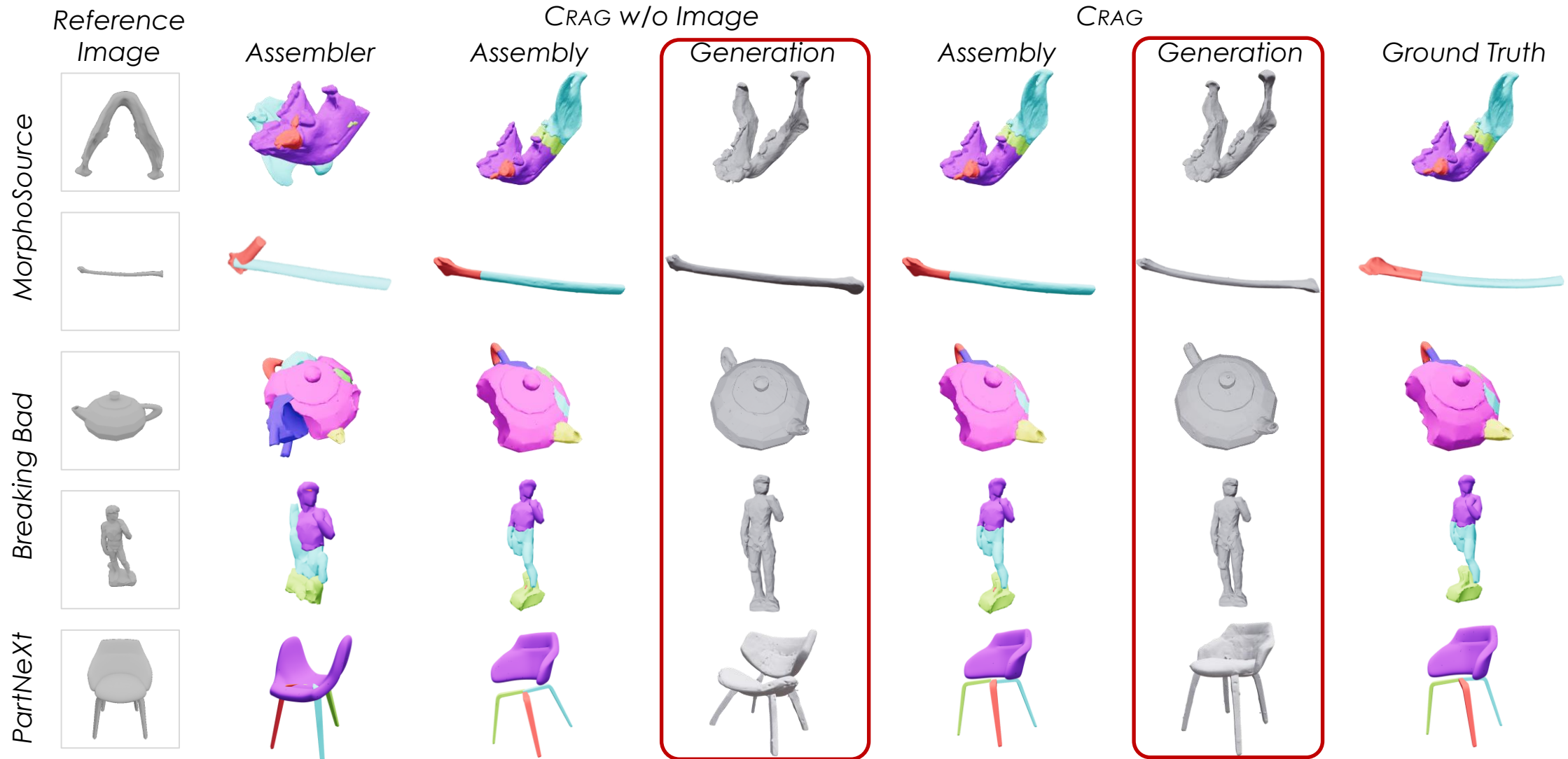
CD: Chamfer Distance

	PartNeXt (Wang et al., 2025a)								Breaking Bad (Sellán et al., 2022)							
Part Status	Complete				Missing				Complete				Missing			
Method	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓
GARF (Li et al., 2025a)	52.52	10.68	58.19	3.10	49.40	9.73	60.71	5.78	8.75	1.72	93.56	0.42	14.59	3.01	85.55	3.43
RPF (Sun et al., 2025)	54.99	29.54	46.17	10.46	42.49	22.95	57.20	8.21	30.59	13.67	80.23	1.01	31.04	14.96	77.05	1.20
CRAG w/o img (Ours)	45.45	9.82	61.67	3.31	42.46	8.70	66.74	5.17	8.00	1.37	94.64	0.22	11.43	1.79	92.03	0.52
Assembler (Zhao et al., 2025a)	85.82	17.14	44.18	27.93	83.80	15.00	49.86	24.71	74.92	13.22	48.38	7.46	74.45	13.43	45.93	7.78
CRAG (Ours)	45.12	9.13	65.89	2.40	42.33	7.86	71.81	4.21	8.00	1.36	94.68	0.21	<u>11.44</u>	1.77	92.07	0.50

Does generation improve assembly by providing a holistic prior?



Can we still assemble the observed parts and synthesize a complete object from incomplete fragment sets?



Can we still assemble the observed parts and synthesize a complete object from incomplete fragment sets?

Fragments	Image Cond.	Generation	GT.
	N/A		
	N/A		
	N/A		

Can we still assemble the observed parts and synthesize a complete object from incomplete fragment sets?

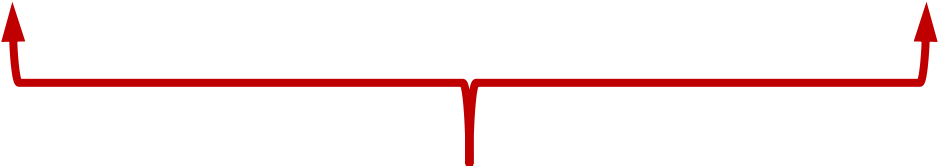
RE: Rotation Error

TE: Translation Error

PA: Part Accuracy

CD: Chamfer Distance

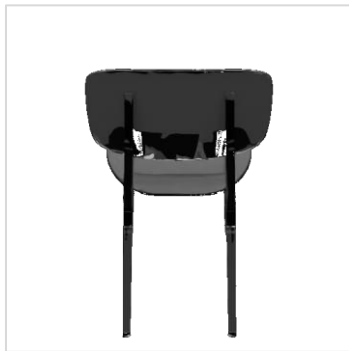
	PartNeXt (Wang et al., 2025a)								Breaking Bad (Sellán et al., 2022)							
Part Status	Complete				Missing				Complete				Missing			
Method	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓	RE ↓	TE ↓	PA ↑	CD ↓
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20% Missing Part

Does part-level evidence help disambiguate image conditioned 3D generation?

Reference Image
with Ambiguity



TripoSG



C
R
A
G
Assembly Generation



Ground Truth



Does part-level evidence help disambiguate image conditioned 3D generation?

CRAG vs 3D Generation Model

Method	CD-L1 ($\times 10^{-2}$) ↓	CD-L2 ($\times 10^{-3}$) ↓	F-Score@1% (%) ↑	F-Score@5% (%) ↑	EMD ($\times 10^{-3}$) ↓	Failure Rate ↓
TripoSG (Li et al., 2025b)	9.12	11.23	14.63	73.18	16.67	25.0% (1157/4626)
CRAG w/o img	9.26	11.46	15.02	72.61	16.96	0%
CRAG	6.53	5.83	20.49	83.87	12.92	0%

CRAG vs 3D Completion Model

Method	CD-L1 ($\times 10^{-2}$) ↓	CD-L2 ($\times 10^{-3}$) ↓	F-Score@1% (%) ↑	F-Score@5% (%) ↑	EMD ($\times 10^{-3}$) ↓
SDFusion (Cheng et al., 2023)	22.51	23.93	1.90	28.58	28.60
MGPC (Liu et al., 2026)	12.59	<u>11.54</u>	12.75	70.54	16.99
CRAG w/o img	<u>12.31</u>	10.32	<u>13.84</u>	<u>74.11</u>	<u>16.12</u>
CRAG	9.39	5.76	18.23	82.82	13.09

Takeaways

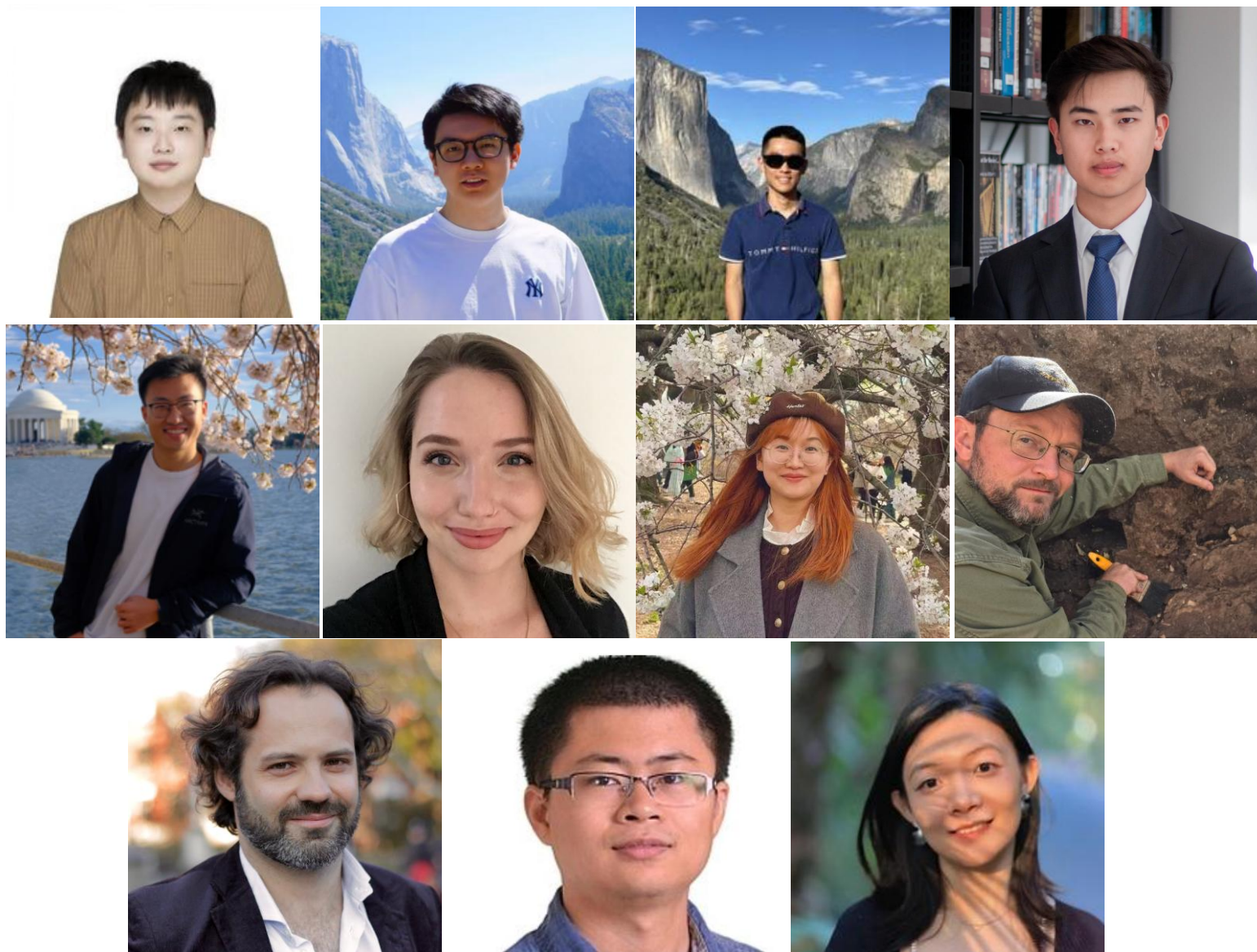
- *Imagining the final global shape really helps 3D assembly.*
- *3D assembly can act as auxiliary task to promote 3D generation model.*
 - *You can try joint training (if you have enough computation resources)*
- *Data / Data Distribution matters in domain-specific 3D assembly, like in archaeology or medicine.*
 - *We observe some overfittings in MorphoSource.*

Future Works

- Data!
 - How to synthesize diverse fragments with controllable fracture surface / simulate the real fracture for different domains.
- Agentic 3D assembly:
 - When you try to assemble object with more than **1000** pieces
 - Extract subgroup
 - Verifier and rewind
 - Combination of end-to-end and optimization-based method
- Language-driven arbitrary-shape assembly
- Learn from human video
 - Physical constraints for assembly
 - Novel object



Thanks!



Project Page



Code Repo