PointMAC: Meta-Learned Adaptation for Robust Test-Time Point Cloud Completion

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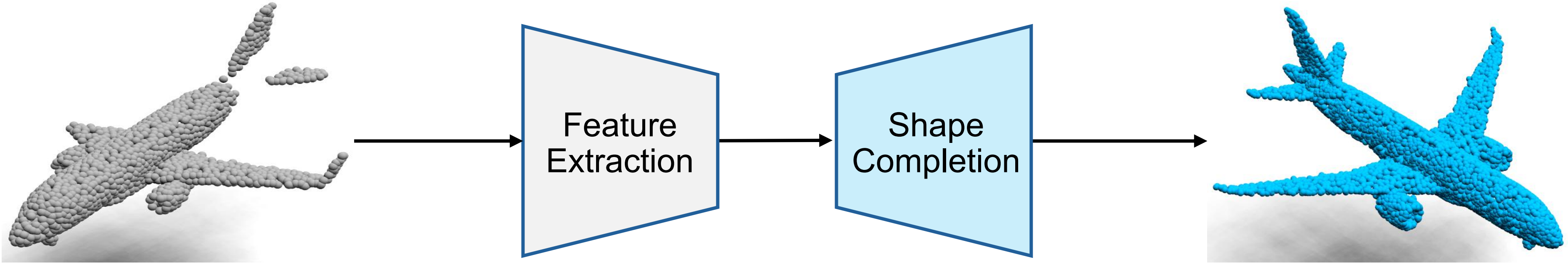
Background: Point Cloud Completion



Input: incomplete shape

Output: complete shape

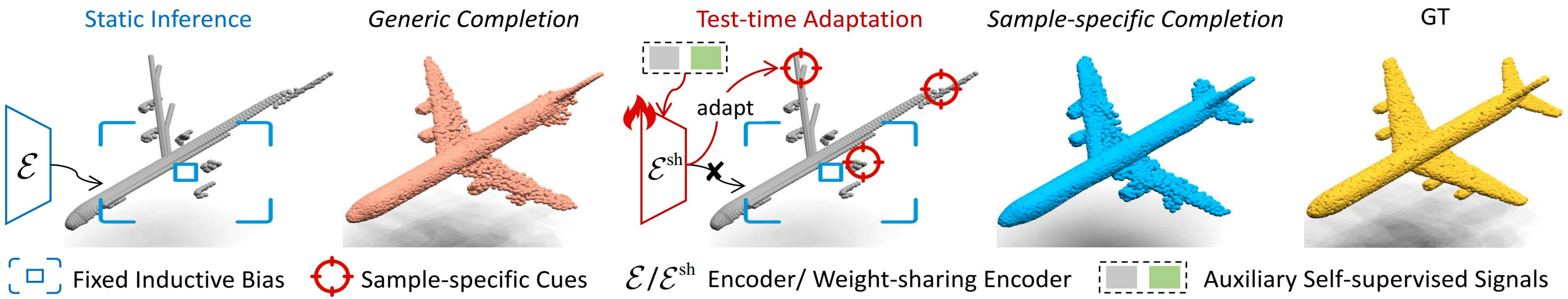
Goal: complete missing parts of a point cloud into a full 3D shape.

Motivation

What's the problem (and why do existing methods fail)?

Static Inference → Generic Completion

- Completion models **frozen at deployment** — infer but never learn
- Relying on **training priors** — **CANNOT** adapt to unseen geometry / noise
- Predicts *plausible* but *non-specific* shapes



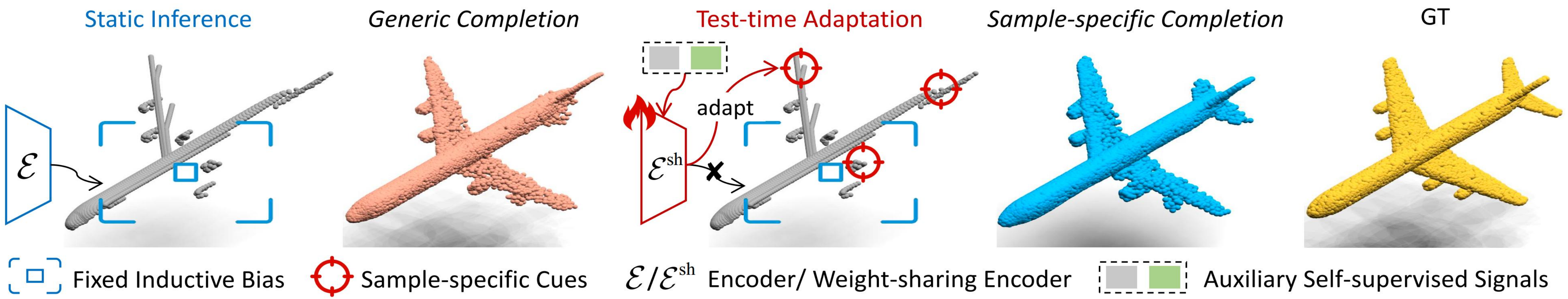
Limitation: (1) static inference and (2) training-learned inductive biases

Motivation

What's our solution?

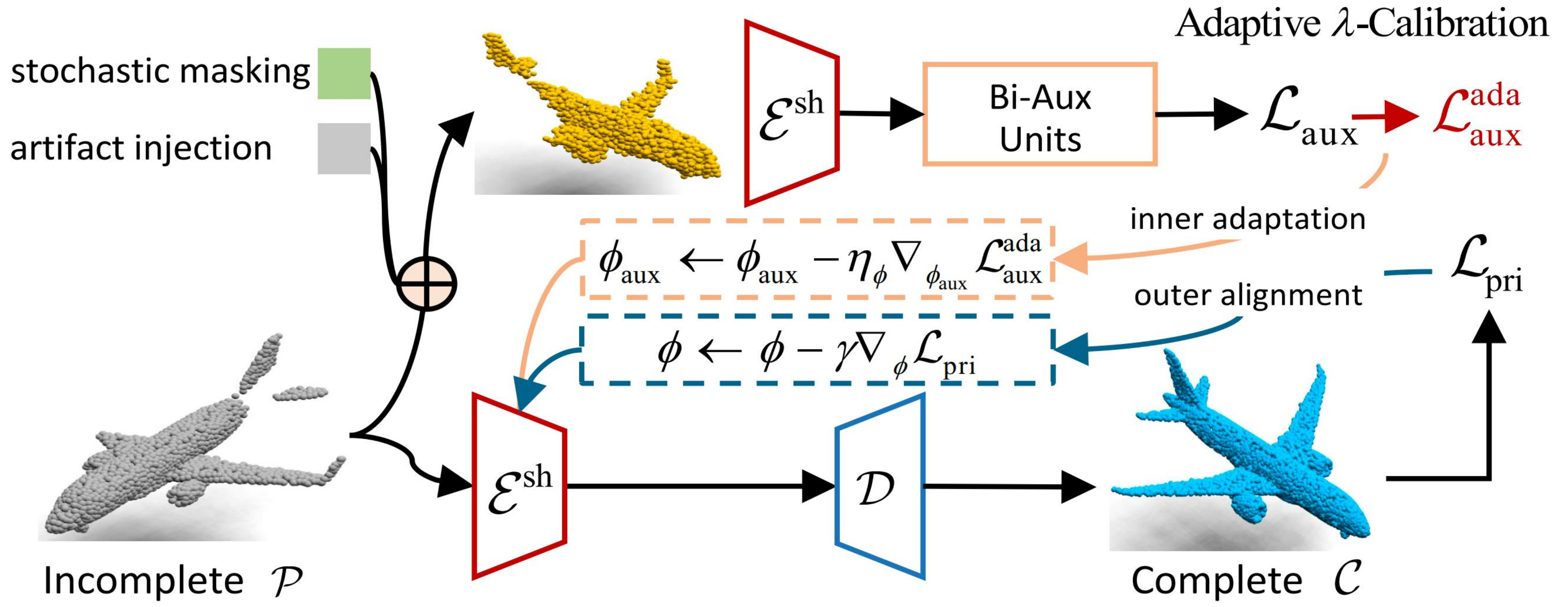
Adapt at Test Time!

- Test-time adaptation (TTA) + meta-auxiliary learning → on-the-fly shared encoder adaptation



Core Challenge: from static inference → adaptive, self-improving completion

PointMAC: Meta-Learned Test-Time Training



(i) **Inner Auxiliary Adaptation**

(ii) **Outer Primary Alignment**

$$\phi_{\mathrm{aux}}^{\mathrm{smr}(t+1)} \leftarrow \phi_{\mathrm{aux}}^{\mathrm{smr}(t)} - \alpha \cdot \nabla_{\phi_{\mathrm{aux}}^{\mathrm{smr}}} \mathcal{L}_{\mathrm{aux}}^{\mathrm{smr}} \left(\widetilde{\mathcal{P}}^{(t)}, \mathcal{P}^{(t)}; \phi_{\mathrm{pri}}^{\mathrm{sh}(t)}, \phi_{\mathrm{aux}}^{\mathrm{sh}(t)}, \phi_{\mathrm{aux}}^{\mathrm{smr}(t)} \right),$$

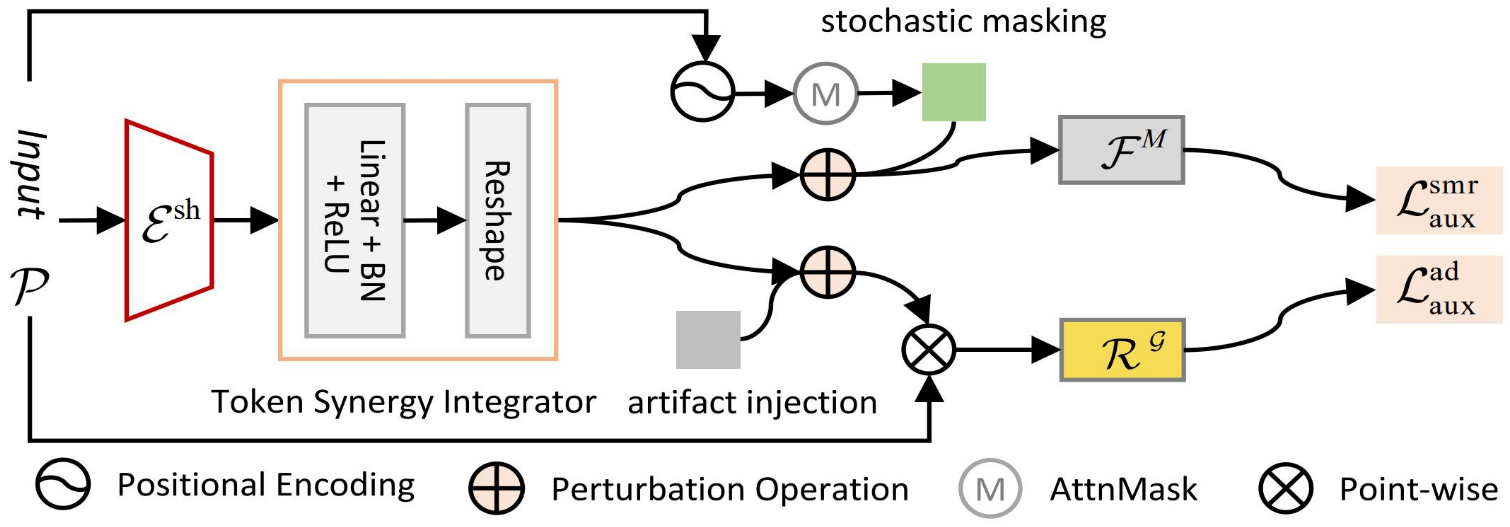
$$\phi_{\mathrm{aux}}^{\mathrm{ad}(t+1)} \leftarrow \phi_{\mathrm{aux}}^{\mathrm{ad}(t)} - \beta \cdot \nabla_{\phi_{\mathrm{aux}}^{\mathrm{ad}}} \mathcal{L}_{\mathrm{aux}}^{\mathrm{ad}} \left(\widehat{\mathcal{P}}^{(t)}, \mathcal{P}^{(t)}; \phi_{\mathrm{pri}}^{\mathrm{sh}(t)}, \phi_{\mathrm{aux}}^{\mathrm{sh}(t)}, \phi_{\mathrm{aux}}^{\mathrm{ad}(t)} \right),$$

$$\boxed{\phi_{\mathrm{pri}}^{(t+1)}} \leftarrow \phi_{\mathrm{pri}}^{(t)} - \gamma \cdot \nabla_{\phi_{\mathrm{pri}}^{(t)}} \left(\frac{1}{T} \sum_{i=1}^{T} \mathcal{L}_{\mathrm{pri}}(\mathcal{C}^{(i)}, \mathcal{P}^{(i)}; \phi_{\mathrm{pri}}^{(t)}) \right).$$

PointMAC: Meta Auxiliary Learning — Bi-Aux Units

- **Bi-Aux Units**: Two Self-Supervised Adaptation Signals

Purpose: on-the-fly adaptation under structural & sensor incompleteness



(1) Stochastic Masked Reconstruction:

randomly mask regions → recover geometry
→ robust to missing parts

$$\mathcal{L}_{\mathrm{aux}}^{\mathrm{smr}} = \mathcal{L}_{\mathrm{CD}}(\widetilde{\mathcal{P}}, \mathcal{P}).$$

(2) Artifact Denoising:

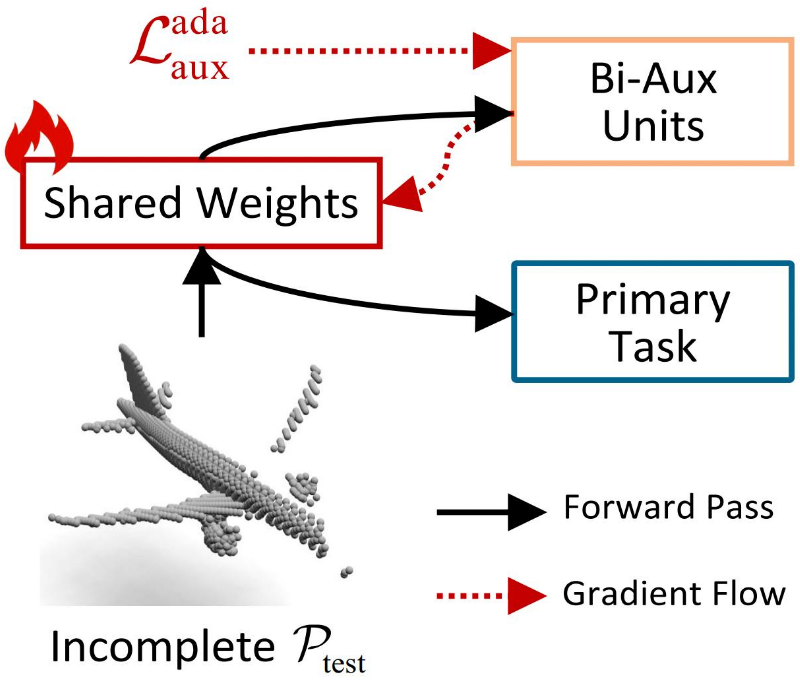
add realistic noise → restore clean structure
→ suppress artifacts

a noisy partial input $\overline{\mathcal{P}} = \mathcal{P} + \mathcal{N}(0, \sigma^2)$

a clean and dense point cloud $\widehat{\mathcal{P}} = \Upsilon_{\varepsilon}^{\mathrm{ad}}(\overline{\mathcal{P}})$

$\mathcal{L}_{\mathrm{aux}}^{\mathrm{ad}} = \mathcal{L}_{CD}(\widehat{\mathcal{P}}, \mathcal{P})$

PointMAC: Sample-Specific Test-Time Adaptation



Algorithm 1: Sample-Specific Test-Time Adaptation

Input: Trained parameters $\phi = \{\phi_{\text{pri}}^{\text{sh}}, \phi_{\text{pri}}, \phi_{\text{aux}}^{\text{sh}}, \phi_{\text{aux}}^{\text{smr}}, \phi_{\text{aux}}^{\text{ad}}\}$;
test input $\mathcal{P}_{\text{test}}$; step size η; number of steps K
Output: Adapted encoder $\phi_{\text{pri}}^{\text{sh}}$

Apply stochastic masking and artifact injection using $\mathcal{M}$ and σ via Aux^{smr} and Aux^{ad};
for $t = 0$ **to** $K-1$ **do** /* Inner-loop adaptation */
- $\widetilde{\mathcal{P}} \leftarrow Aux^{\text{smr}}$_Forward$(\mathcal{P}_{\text{test}}, \mathcal{M}; \phi_{\text{aux}}^{\text{smr}})$;
- $\widehat{\mathcal{P}} \leftarrow Aux^{\text{ad}}$_Forward$(\mathcal{P}_{\text{test}}, \sigma; \phi_{\text{aux}}^{\text{ad}})$;
- $\boxed{\mathcal{L}_{\text{aux}}^{\text{ada}} \leftarrow \lambda_{\text{smr}} \cdot \mathcal{L}_{\text{aux}}^{\text{smr}}(\widetilde{\mathcal{P}}, \mathcal{P}_{\text{test}}) + \lambda_{\text{ad}} \cdot \mathcal{L}_{\text{aux}}^{\text{ad}}(\widehat{\mathcal{P}}, \mathcal{P}_{\text{test}});}$
- $\phi_{\text{pri}}^{\text{sh}(t+1)} \leftarrow \phi_{\text{pri}}^{\text{sh}(t)} - \eta \cdot \nabla_{\phi_{\text{pri}}^{\text{sh}}} \mathcal{L}_{\text{aux}}^{\text{ada}}$; /* Gradient descent on shared encoder */

return $\phi_{\text{pri}}^{\text{sh}(K)}$

Adaptive λ-Calibration. dynamically adjusts the auxiliary weights λ_{smr} and λ_{ad}

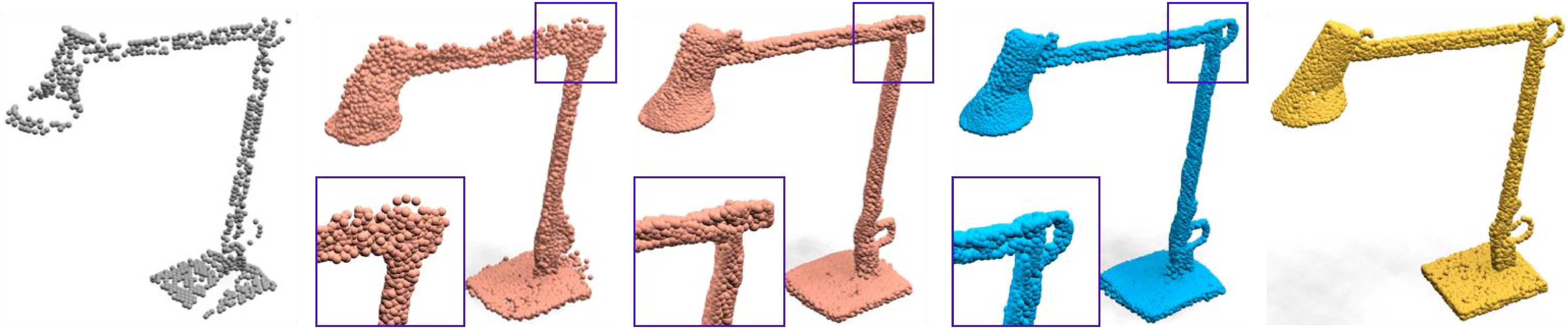
$$w_{\text{smr}} = \left(\log(1+\lambda_{\text{smr}}^2) / \left[\log(1+\lambda_{\text{smr}}^2) + \log(1+\lambda_{\text{ad}}^2)\right]\right), \quad w_{\text{ad}} = 1 - w_{\text{smr}}, \tag{6}$$

$$\mathcal{L}_{\text{aux}}^{\text{ada}} = w_{\text{smr}} \cdot \mathcal{L}_{\text{aux}}^{\text{smr}} + w_{\text{ad}} \cdot \mathcal{L}_{\text{aux}}^{\text{ad}}. \tag{7}$$

Both the auxiliary branch parameters $\phi_{\text{aux}} = \{\phi_{\text{aux}}^{\text{smr}}, \phi_{\text{aux}}^{\text{ad}}\}$ and the weighting coefficients $\lambda \in \{\lambda_{\text{smr}}, \lambda_{\text{ad}}\}$ are jointly updated via gradient descent:

$$\phi_{\text{aux}} \leftarrow \phi_{\text{aux}} - \eta_{\phi} \nabla_{\phi_{\text{aux}}} \mathcal{L}_{\text{aux}}^{\text{ada}}, \quad \lambda \leftarrow \lambda - \eta_{\lambda} \nabla_{\lambda} \mathcal{L}_{\text{aux}}^{\text{ada}}. \tag{8}$$

PointMAC: Ablation



Input | Baseline | w/ Bi-Auxiliary Units | Full Model | GT

Generic completion
(One-size-fits-all)

Sample-specific completion
(Test-time Adaptation)

PointMAC: Main Experiment Results

PointMAC is among the most thoroughly evaluated methods, covering synthetic (ShapeNet, PCN), simulated (MVP), and real-world (KITTI) benchmarks, and it achieves new SOTA performance.

Table 1: Synthetic experiments on the ShapeNet dataset.

CD-ℓ_2($\times$1000)	Table	Chair	Plane	Car	Sofa	Bird House	Bag	Remote	Key board	Rocket	CD-S	CD-M	CD-H	CD-Avg	F1
FoldingNet [18]	2.53	2.81	1.43	1.98	2.48	4.71	2.79	1.44	1.24	1.48	2.67	2.66	4.05	3.12	0.082
PCN [4]	2.13	2.29	1.02	1.85	2.06	4.50	2.86	1.33	0.89	1.32	1.94	1.96	4.08	2.66	0.133
PoinTr [7]	0.81	0.95	0.44	0.91	0.79	1.86	0.93	0.53	0.38	0.57	0.58	0.88	1.79	1.09	0.464
SnowflakeNet [5]	0.75	0.84	0.42	0.88	0.72	1.74	0.81	0.48	0.36	0.51	0.52	0.80	1.62	0.98	0.477
SeedFormer [6]	0.72	0.81	0.40	0.89	0.71	-	-	-	-	-	0.50	0.77	1.49	0.92	0.472
ProxyFormer [8]	0.70	0.83	0.34	**0.78**	0.69	-	-	-	-	-	0.49	0.75	1.55	0.93	0.483
EINet [39]	0.66	0.79	0.41	0.84	0.69	1.49	0.73	0.42	0.33	0.49	0.49	0.75	1.46	0.90	0.432
CRA-PCN [19]	0.66	0.74	0.37	0.85	0.66	1.36	0.73	0.43	0.35	0.50	0.48	0.71	1.37	0.85	-
Ous	**0.65**	**0.72**	**0.34**	0.80	**0.64**	**1.34**	**0.72**	**0.40**	**0.31**	**0.47**	**0.47**	**0.69**	**1.34**	**0.83**	**0.490**

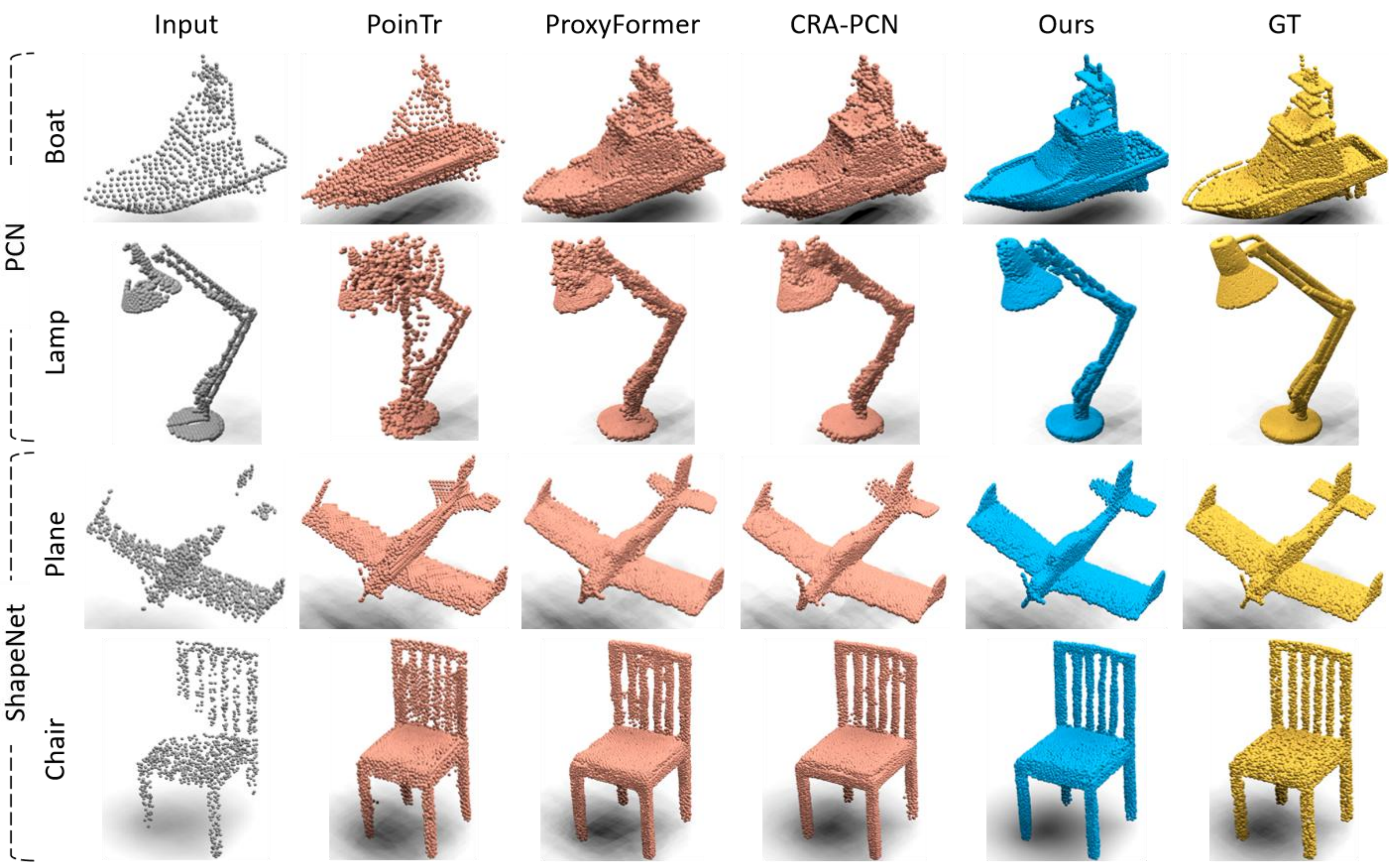
Table 2: Simulated experiments on the MVP dataset.

	PCN [4]	TopNet [41]	MSN [42]	CDN [43]	ECG [44]	VRCNet [38]	CRA-PCN [19]	Ours
CD-ℓ_2 $\downarrow$	9.77	10.11	7.90	7.25	6.64	5.96	5.33	**5.24**
F1 $\uparrow$	0.320	0.308	0.432	0.434	0.476	0.499	0.529	**0.537**

Table 3: Real-world experiments on the KiTTI dataset.

	PCN [4]	FoldingNet [18]	TopNet [41]	GRNet [45]	PoinTr [7]	SeedFormer [6]	ProxyFormer [8]	EINet [39]	Ours
Fidelity $\downarrow$	2.235	7.467	5.354	0.816	**0.000**	0.151	**0.000**	1.48	0.135
MMD $\downarrow$	1.366	0.537	0.636	0.568	0.526	0.516	0.508	0.512	**0.477**

PointMAC: Main Experiment Results



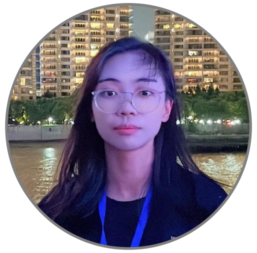
PointMAC: Conclusion

Project Page

This work overcomes the limits of ***static inference*** and ***training priors*** through meta-learned ***test-time adaptation***, enabling robust point cloud completion.

- A ***paradigm shift*** from traditional static, one-size-fits-all inference.
- Robust to ***domain shift*** in real-world deployment.
- A ***generalizable, plug-and-play*** test-time adaptation framework for diverse 3D tasks.

Paper: https://arxiv.org/abs/2510.10365



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