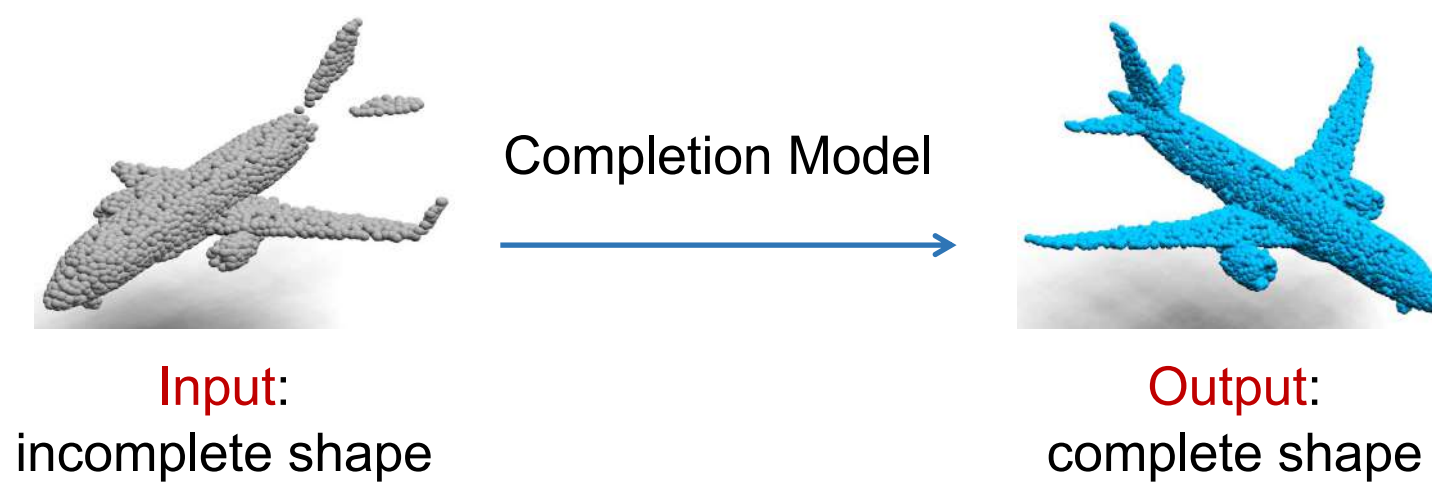


TL;DR: This work overcomes the limits of *static inference* and *training priors* through meta-learned *test-time adaptation*, enabling robust point cloud completion across *synthetic*, *simulated*, and *real-world* datasets.

What's the task?

Point Cloud Completion: Given a partial point cloud $\mathcal{P} = \{\mathbf{p}_i\}_{i=1}^M \subset \mathbb{R}^3$ the goal is to reconstruct a complete point cloud $\mathcal{C} = \{\mathbf{c}_j\}_{j=1}^N \subset \mathbb{R}^3$ with $N > M$.



Motivation

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

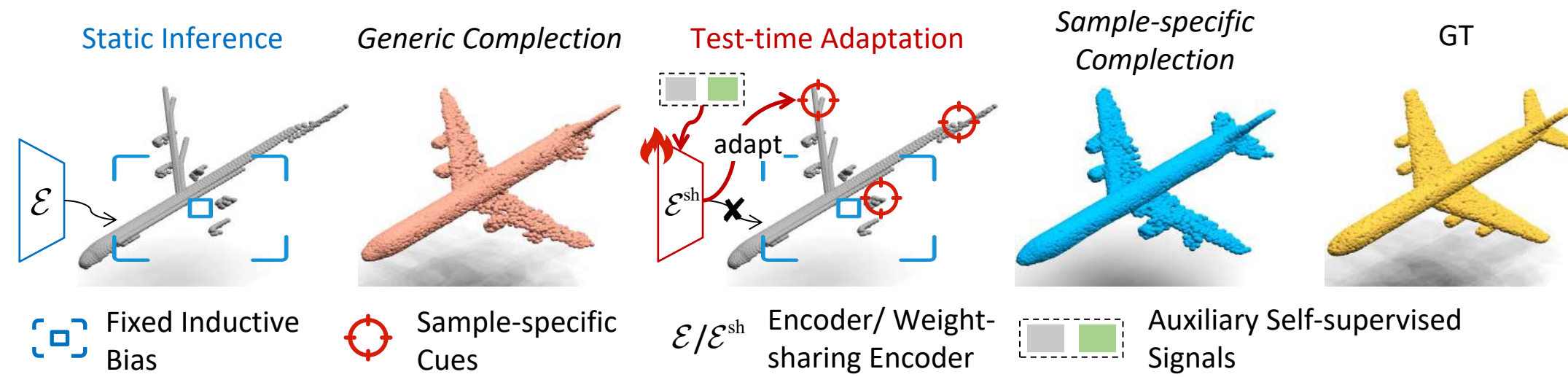
Static Inference → *Generic Completion*

- 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

2. 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

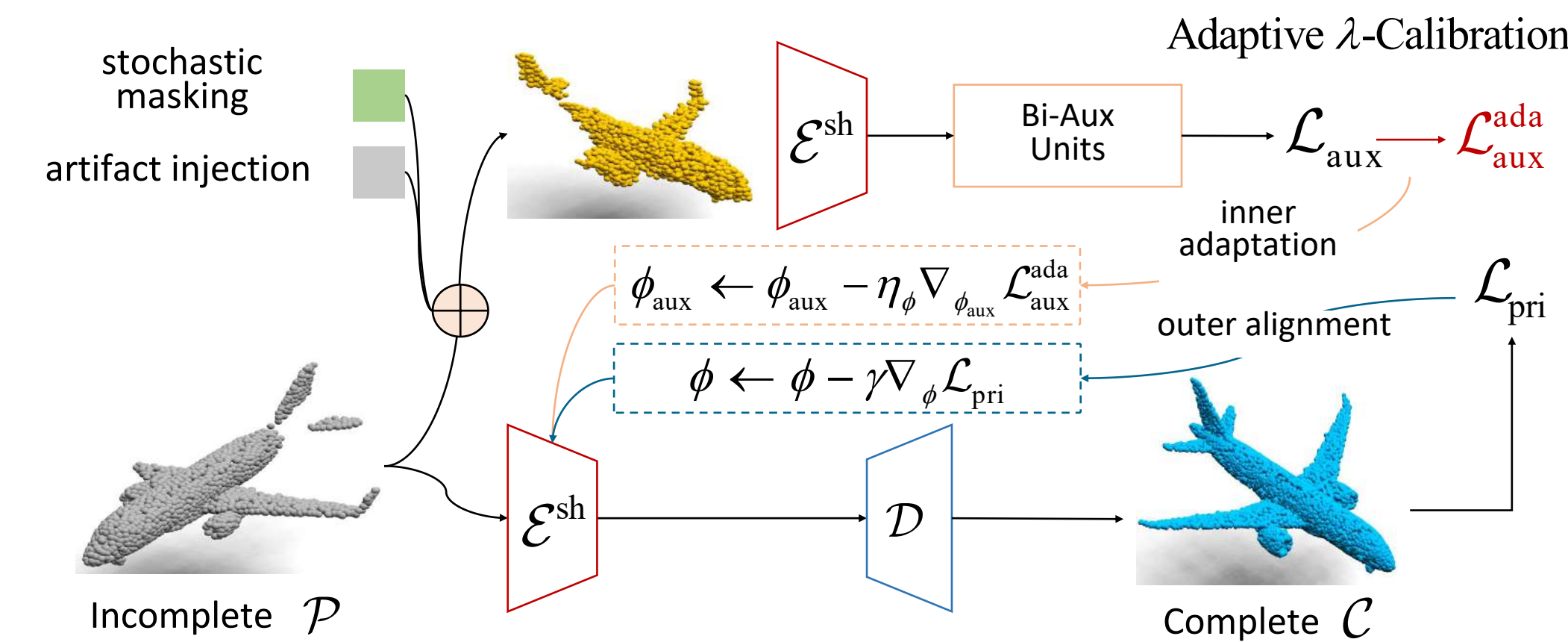


Key Insight

- 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.

Method

Method overview. PointMAC performs meta-learned test-time adaptation for point cloud completion.



Bi-Aux Units. Two Self-Supervised Adaptation Signals

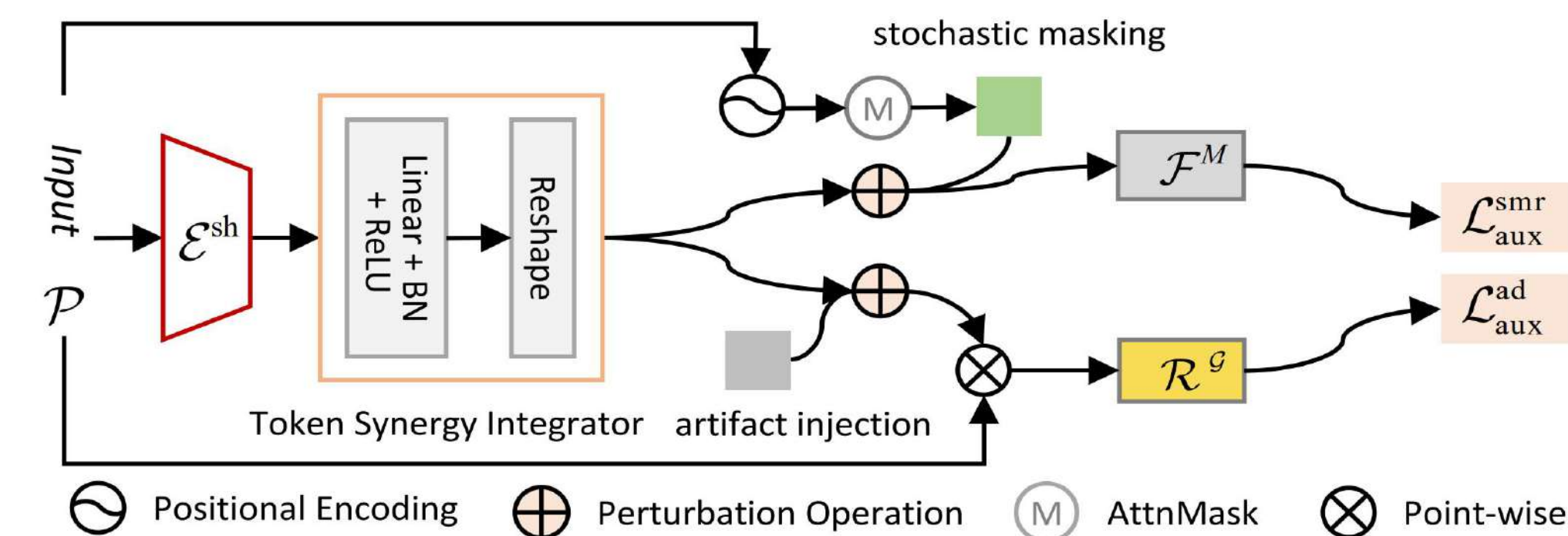
• Stochastic Masked Reconstruction:

randomly mask regions → recover geometry → robust to missing parts

• Artifact Denoising:

add realistic noise → restore clean structure → suppress artifacts

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



Model Learning.

(i) Inner Auxiliary Adaptation:

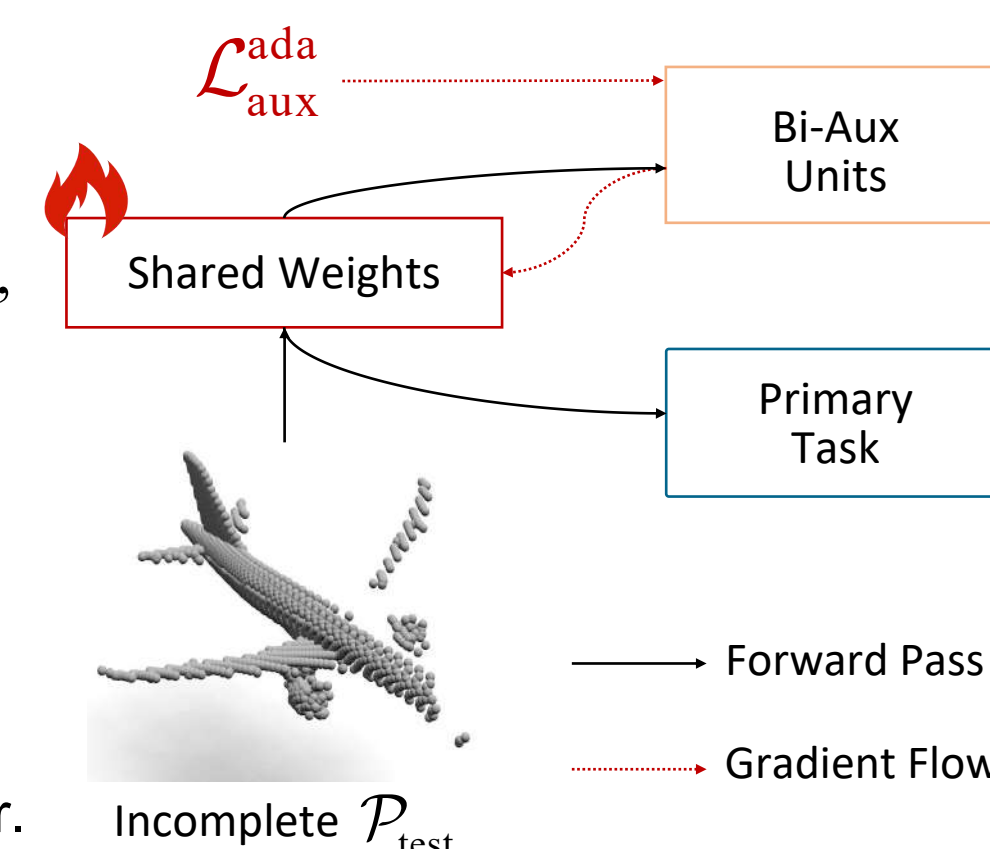
$$\phi_{aux}^{smr(t+1)} \leftarrow \phi_{aux}^{smr(t)} - \alpha \nabla_{\phi_{aux}^{smr}} \mathcal{L}_{aux}^{smr}$$

$$\phi_{aux}^{ad(t+1)} \leftarrow \phi_{aux}^{ad(t)} - \beta \nabla_{\phi_{aux}^{ad}} \mathcal{L}_{aux}^{ad}$$

(ii) Outer Primary Alignment:

$$\phi_{pri}^{(t+1)} \leftarrow \phi_{pri}^{(t)} - \gamma \nabla_{\phi_{pri}^{(t)}} \mathcal{L}_{pri}$$

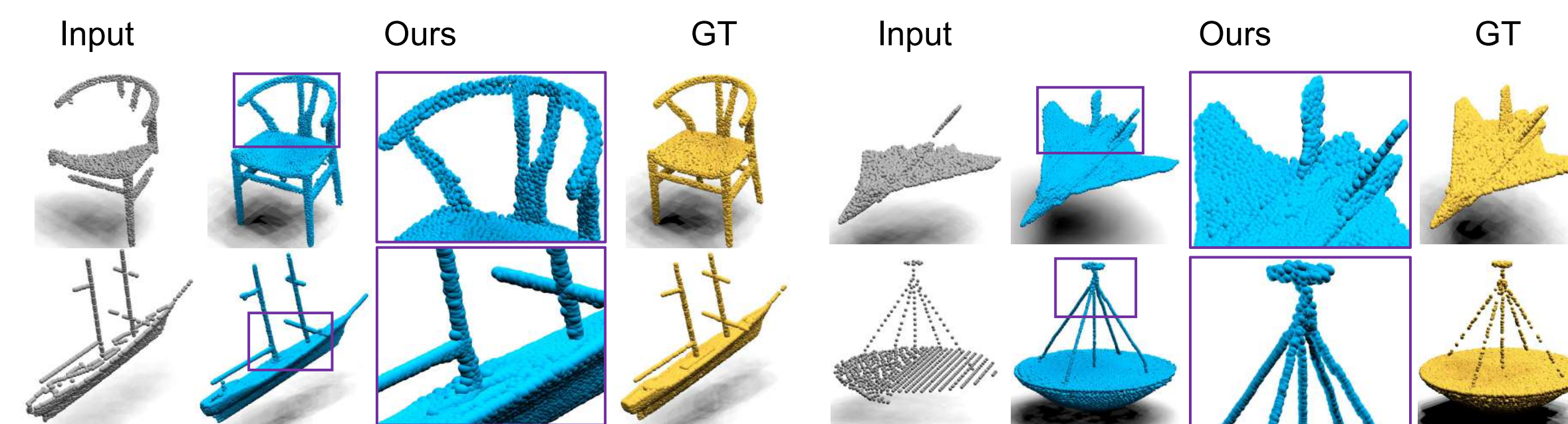
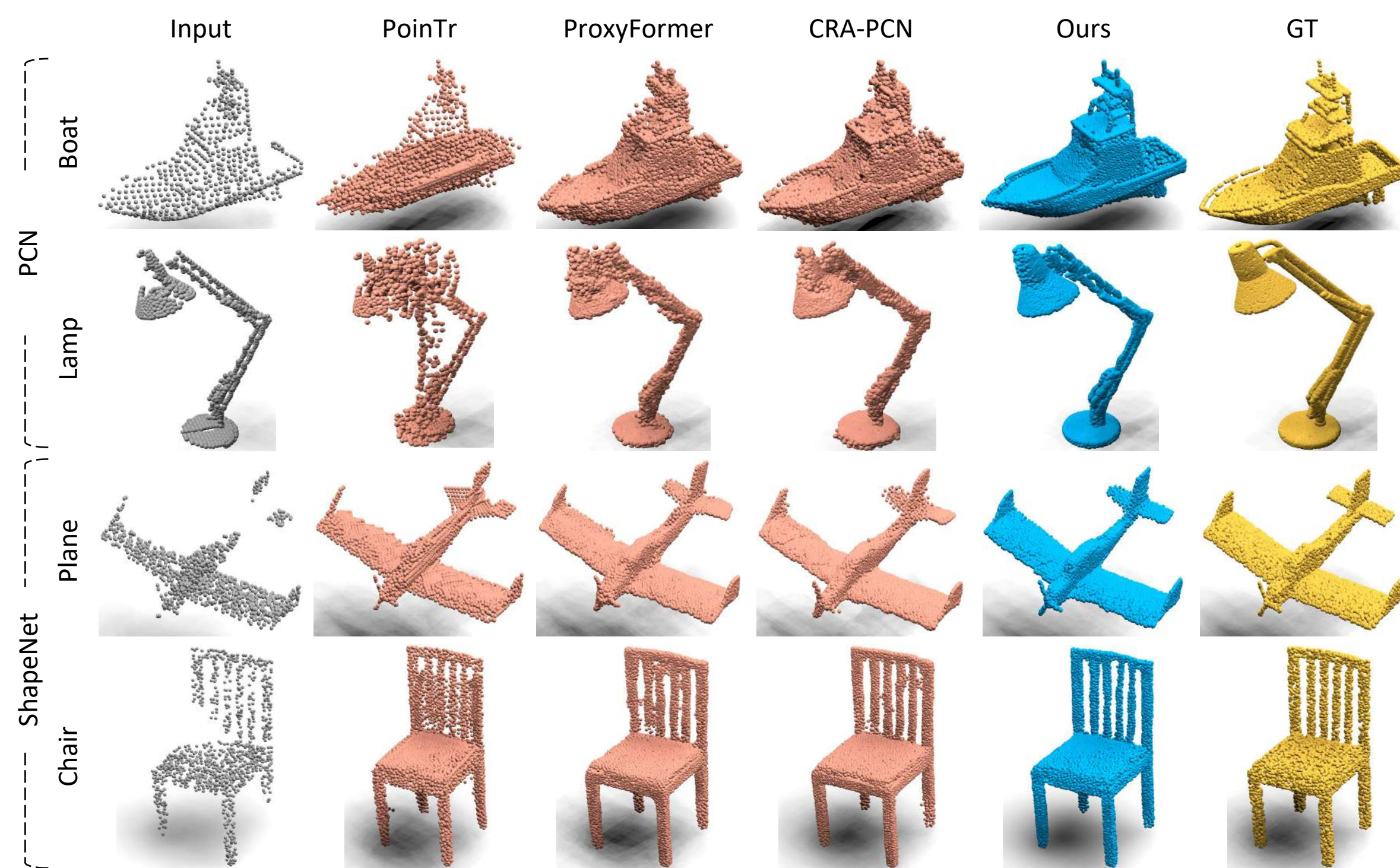
Gradient descent update on shared encoder.



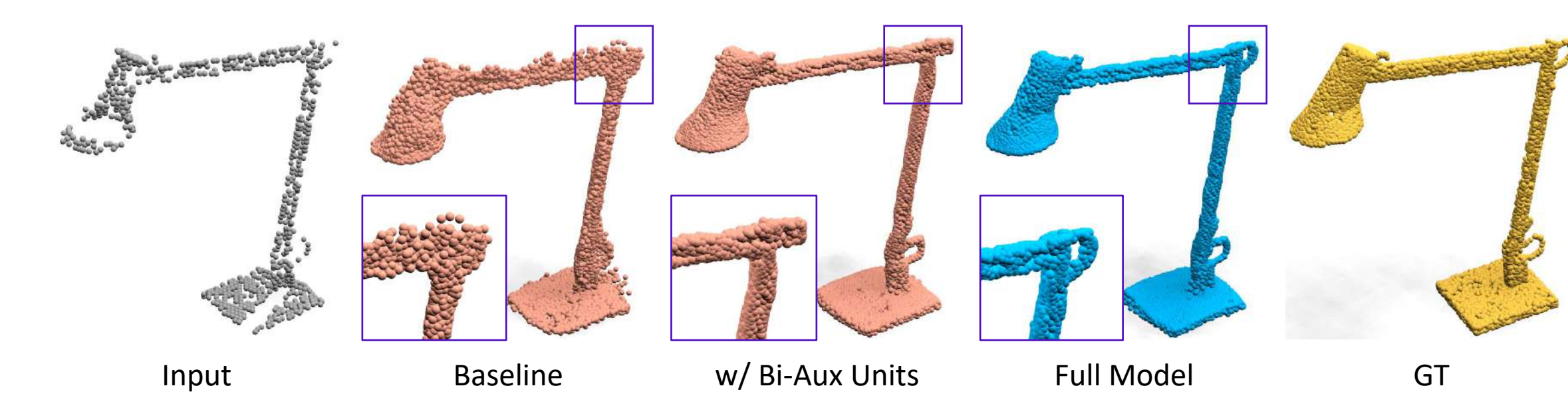
Experiments

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

Visualization results on the PCN and ShapeNet datasets.



Ablation study. Different components of our framework.



Generic completion (One-size-fits-all)

Sample-specific completion (TTA)