



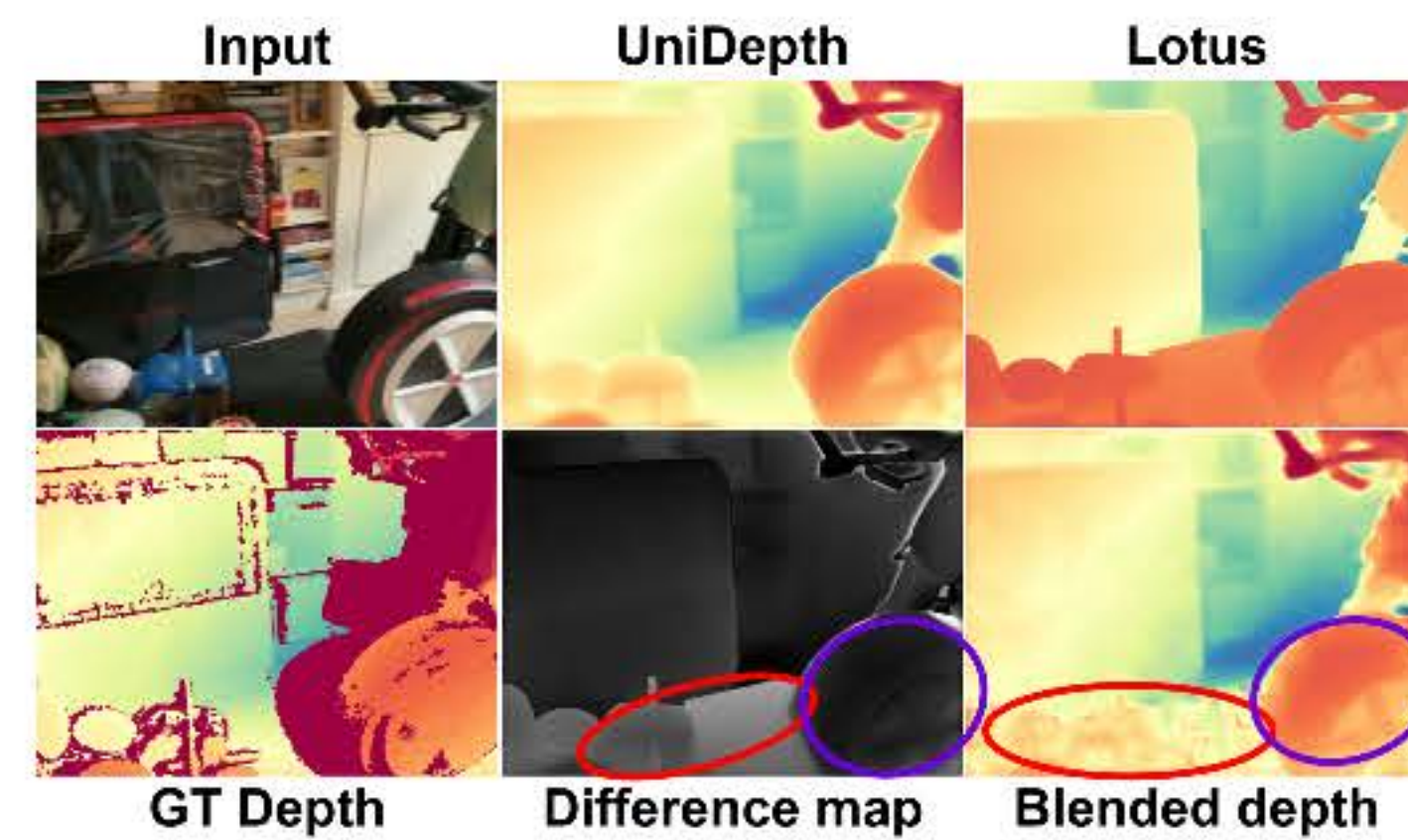
Problem Statement:

- Metric Depth Estimator are **metrically** accurate, but lack details
- Affine-invariant Diffusion Depth Estimator are **detailed, easy to fine-tune**, but lack **metric** information and accuracy
- **SharpDepth**: combining metric and diffusion models to get the best of both worlds



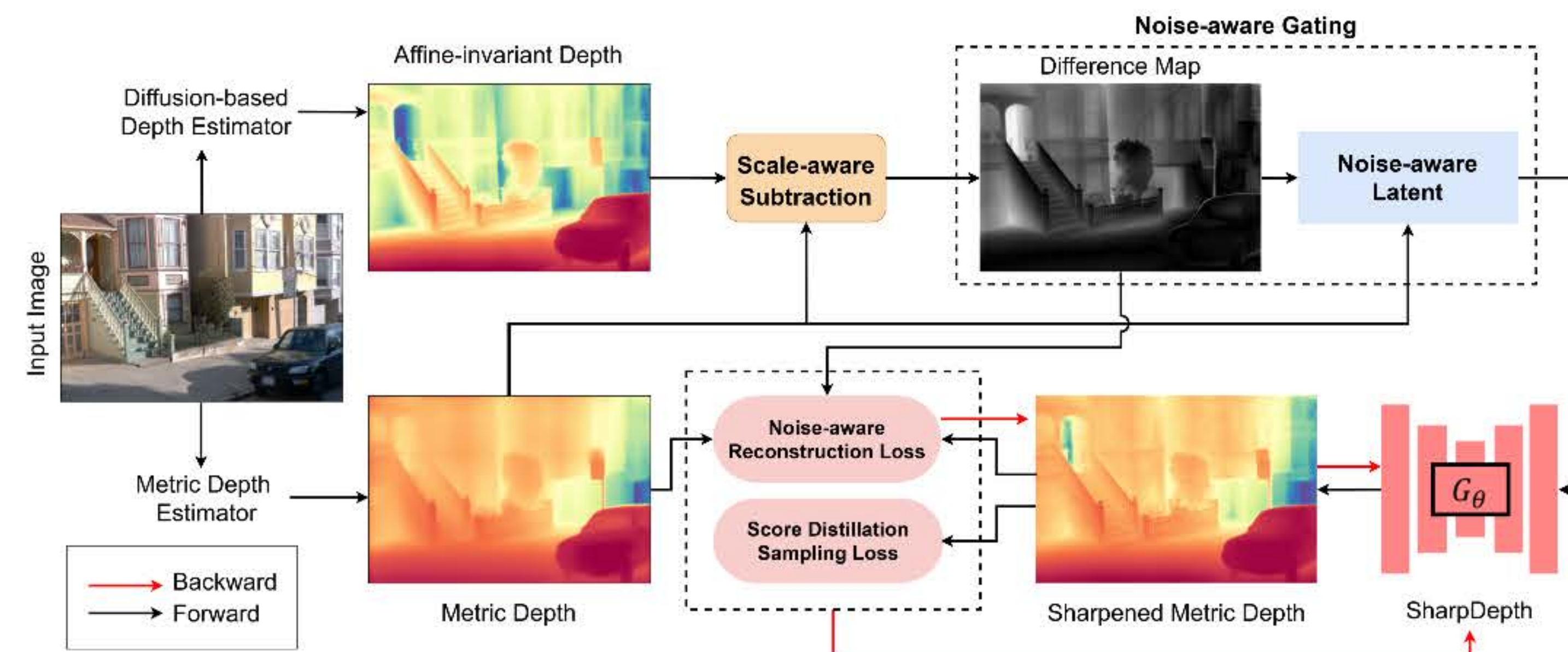
Intuition:

Per-pixel difference between two depth estimators → A measure of boundary sharpness

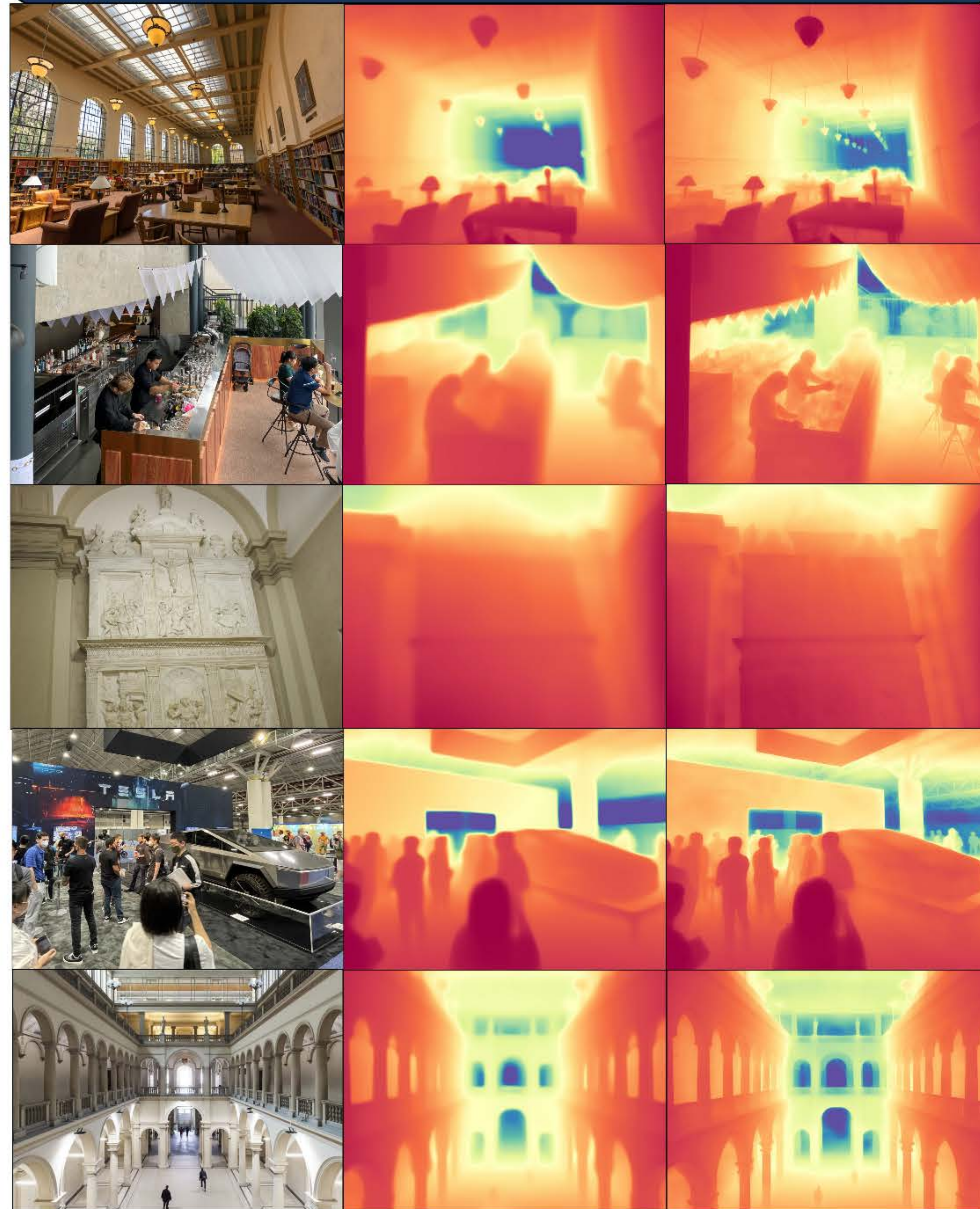


Methodology:

- SDS loss: adding diffusion-like details to predictions
- Reconstruction loss: maintaining accuracy of original metric predictions



Get accurate and sharp metric depth with minimal fine-tuning (no ground-truths needed)



near far

Quantitative Results

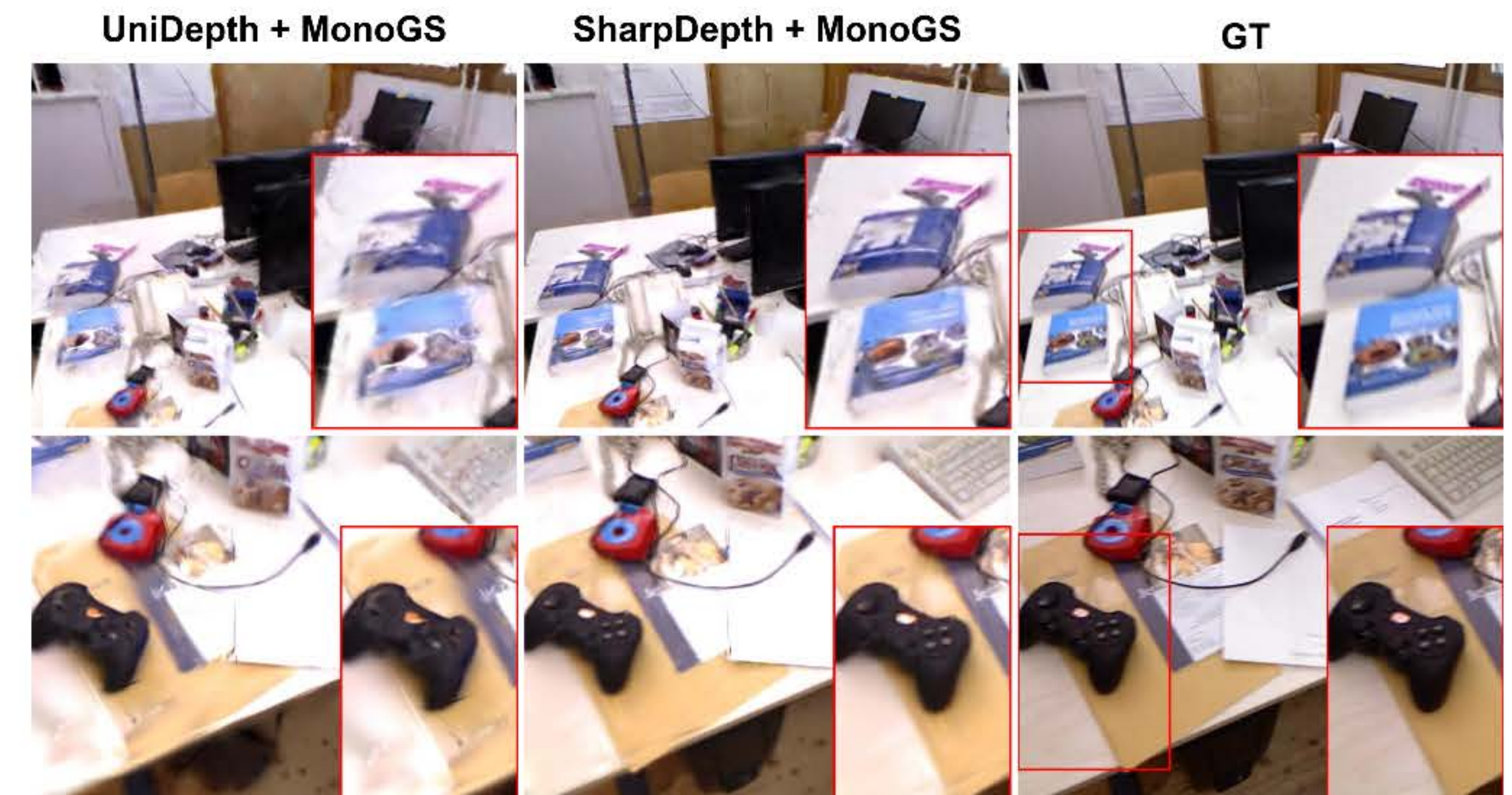
Method	KITTI	NYUv2	Diode	Booster	nuScenes
UniDepth [21]	97.9	98.4	66.0	28.0	83.8
ZoeDepth [2]	96.5	95.2	30.2	20.8	21.8
Metric3Dv2 [14]	97.6	97.4	88.8	15.5	84.2
DAv2-Metric [35]	85.3	1.0	22.0	1.0	19.1
SharpDepth (ours)	97.3	96.9	61.5	27.7	78.5

Table 1. Comparison for percentage of inlier pixels (δ_1) - higher percentage represents better accuracy. We ranked methods as **best**, **second-best**, and **third-best**.

Method	Sintel	Unreal4K	Spring
UniDepth [21]	3.73	8.65	5.29
ZoeDepth [2]	3.35	5.39	4.05
Metric3Dv2 [14]	1.92	2.75	1.78
DAv2-Metric [35]	1.51	2.47	1.36
SharpDepth (ours)	1.94	1.37	1.24

Table 2. Comparison for depth boundary error e_{DBE}^{DBE} - lower errors represents better sharpness. We ranked methods as **best**, **second-best**, and **third-best**.

Applications to Gaussian Splatting SLAM



In-the-wild 3D point-clouds

