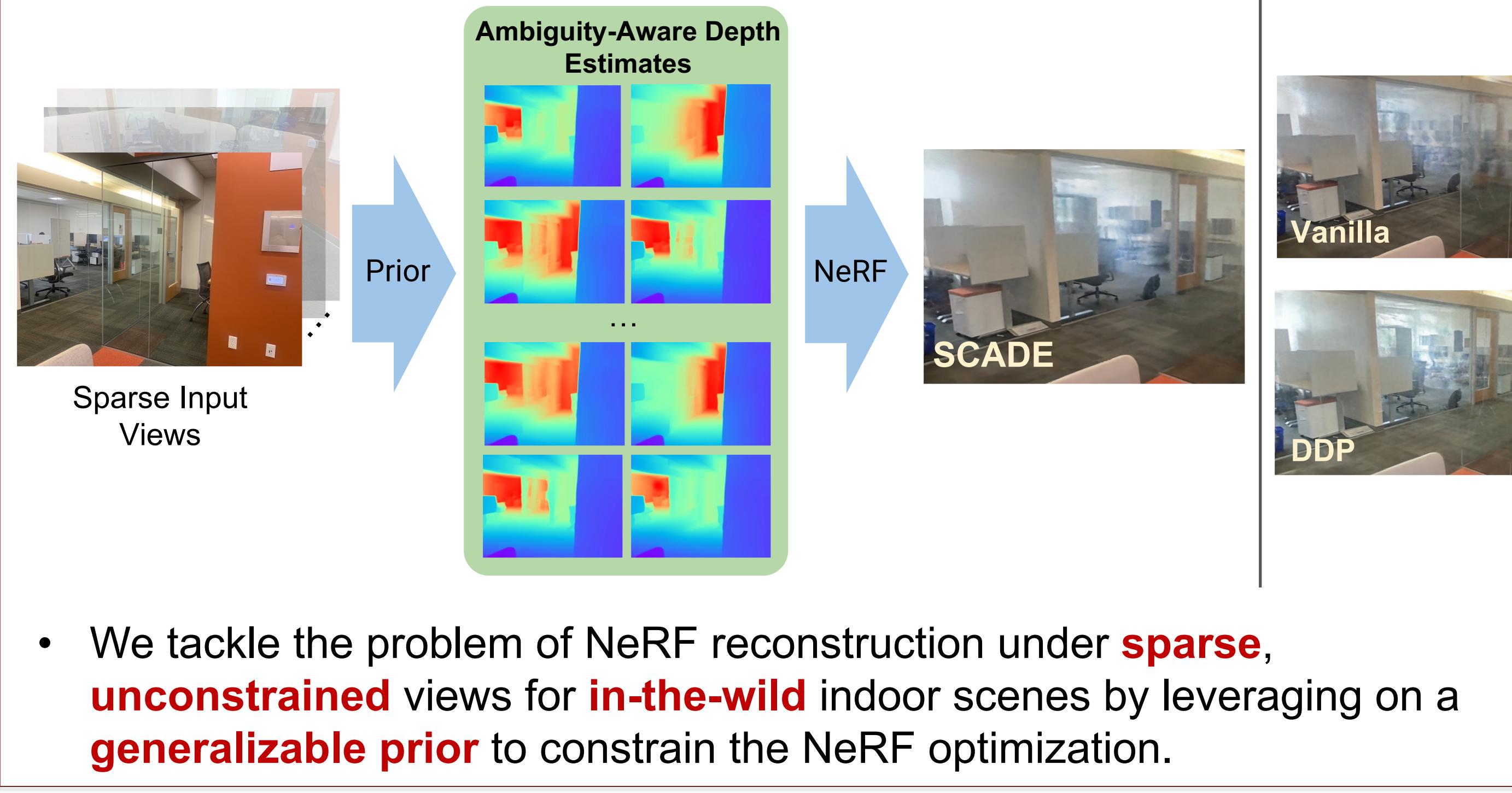


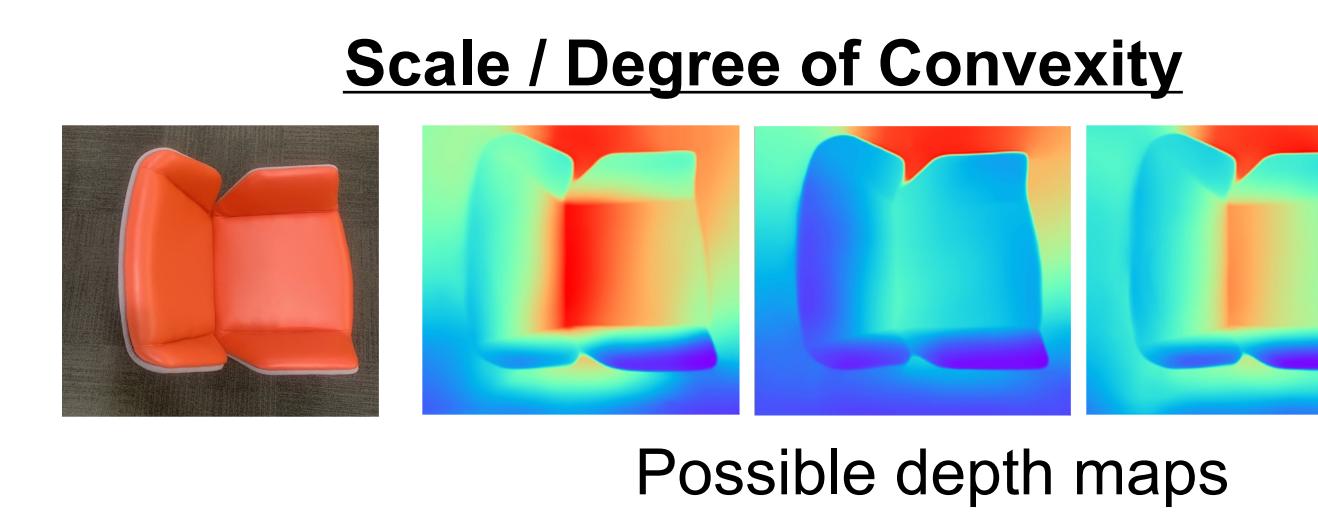
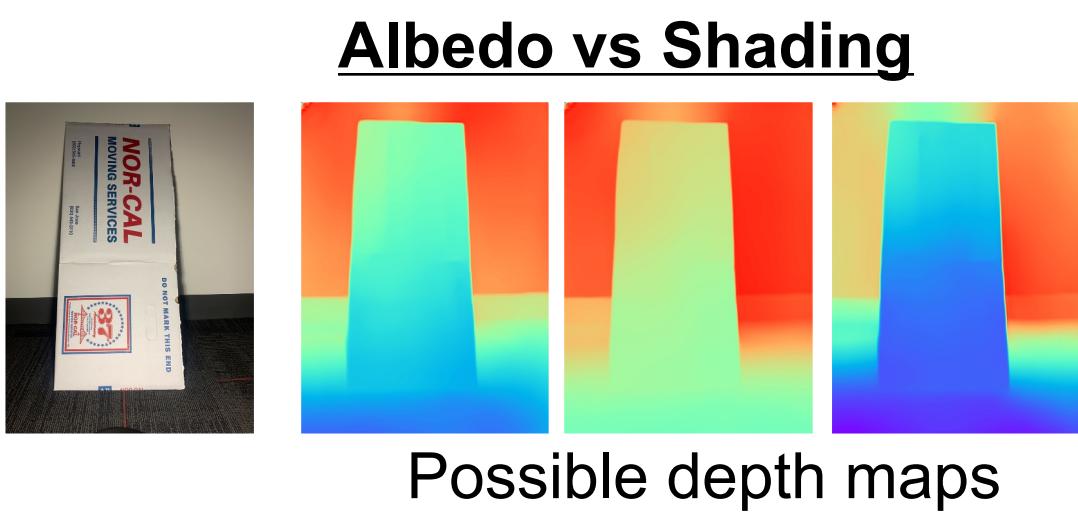


PROBLEM OVERVIEW

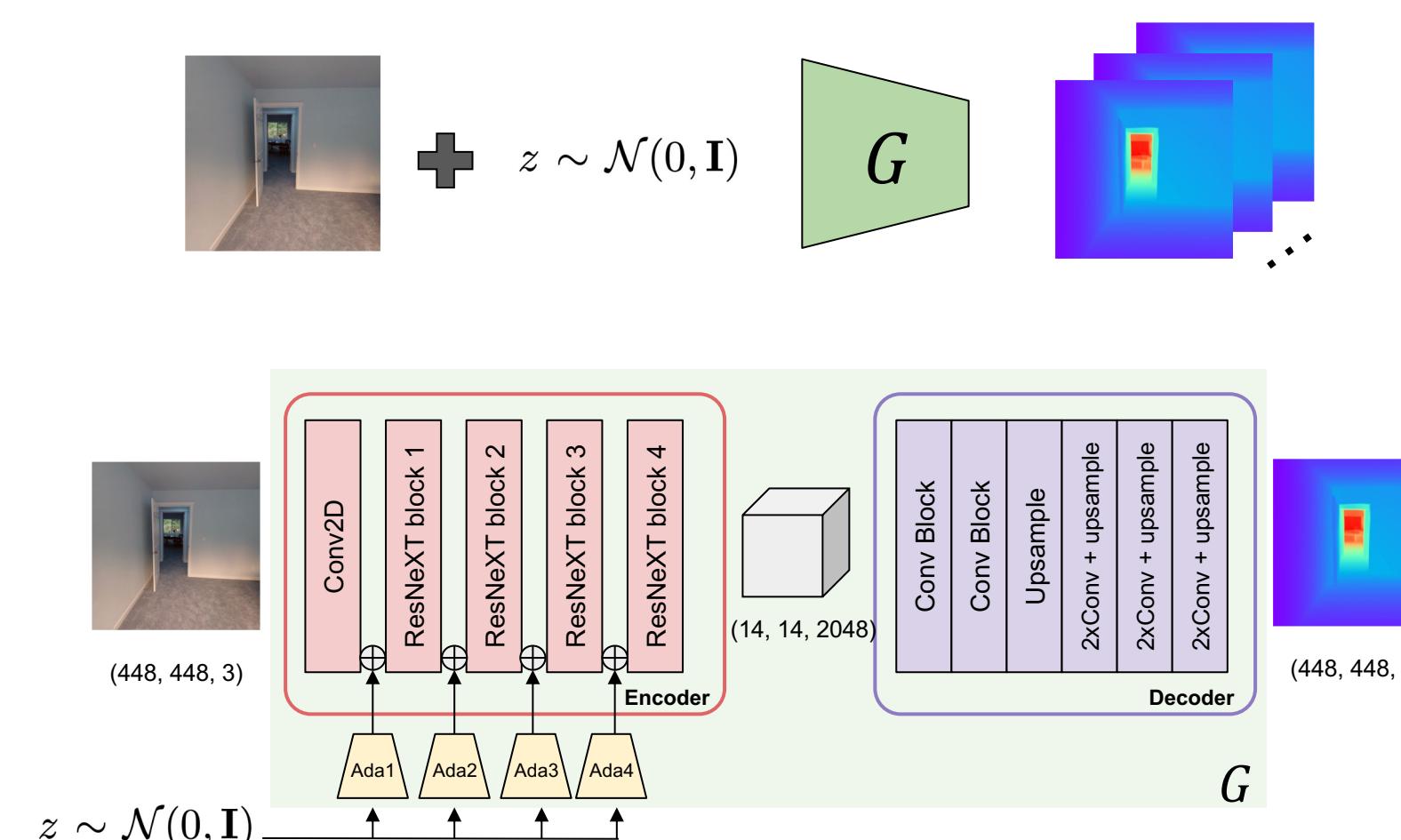


AMBIGUITY-AWARE PRIOR

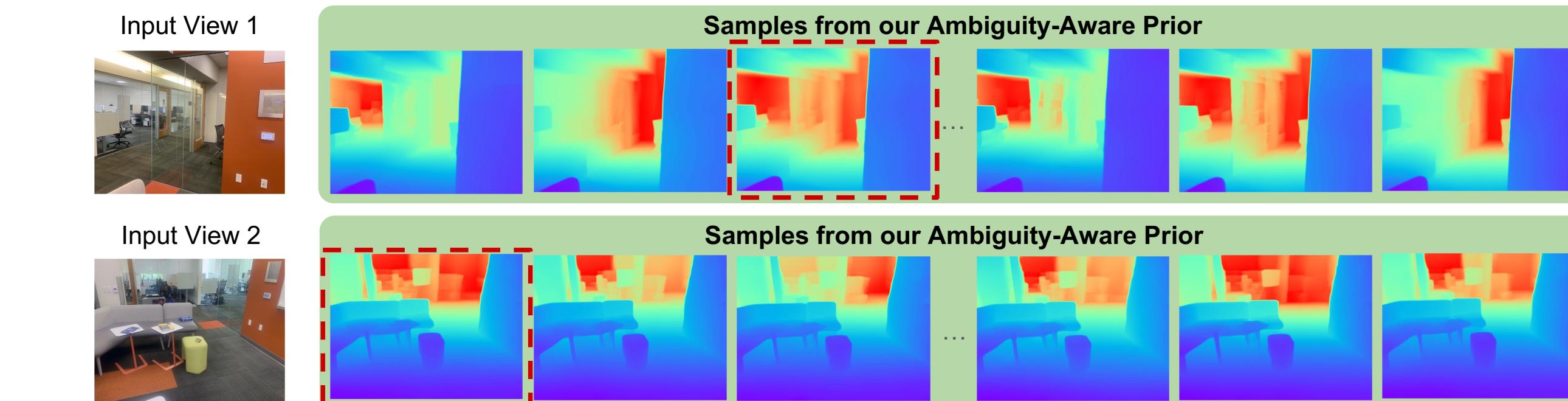
- Monocular depth [1] is generalizable, but is inherently **ambiguous**:



- To handle the ambiguity, we represent depth as a **distribution**, which can be multimodal, by leveraging on **conditional implicit maximum likelihood estimation (cIMLE)** [2].



OUR APPROACH: SCADE

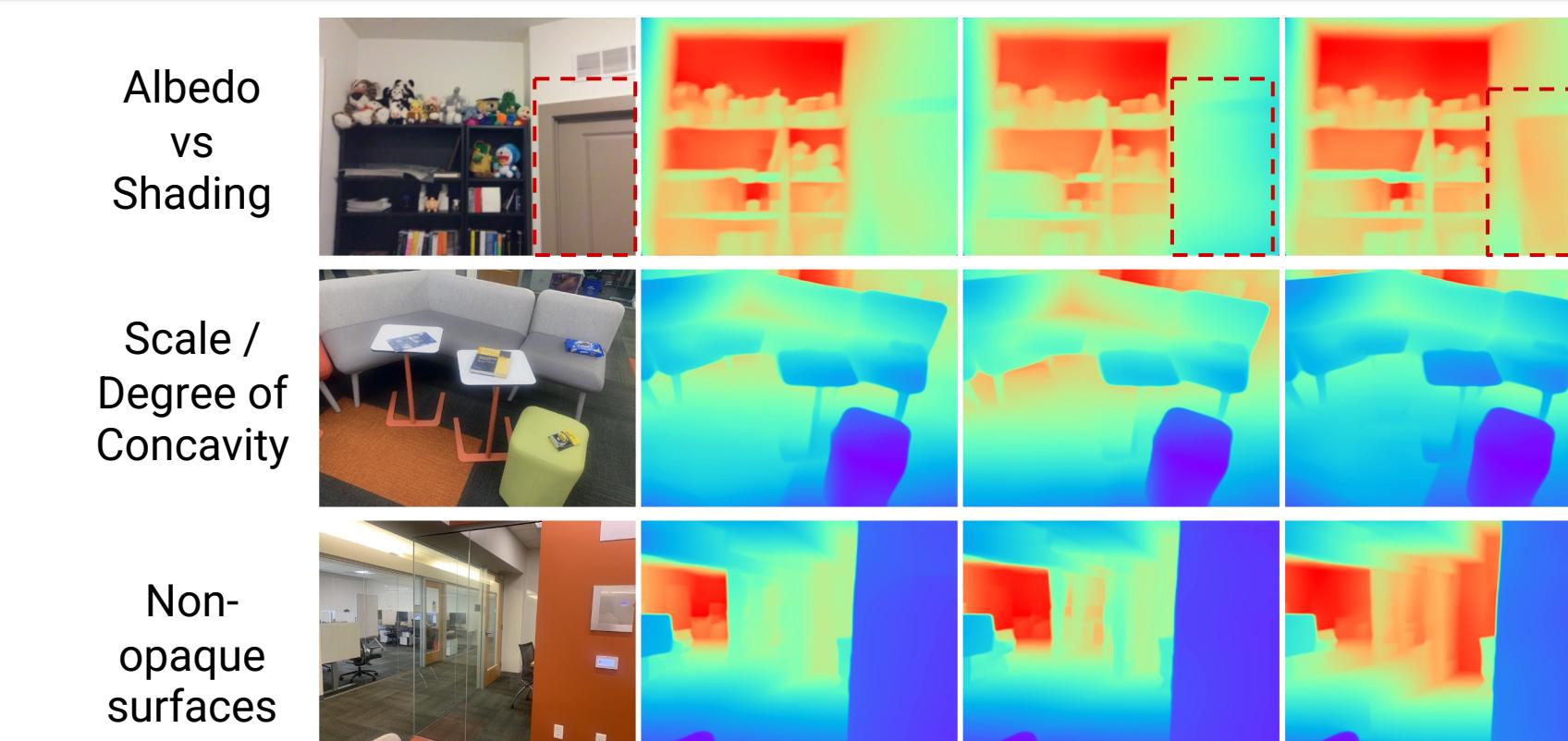


- Inspired by classical **space carving** [3], our loss **fuses** information from multiple views.
- It is **mode seeking** and **sample-based**, leading to supervision in 3D instead of 2D moments.

$$\mathcal{L}_{\text{space_carving}}(\mathbf{r}) = \sum_{i \in [N]} \min_{j \in [M]} \| \mathbf{x}_i - \mathbf{y}_j \|_2^2$$

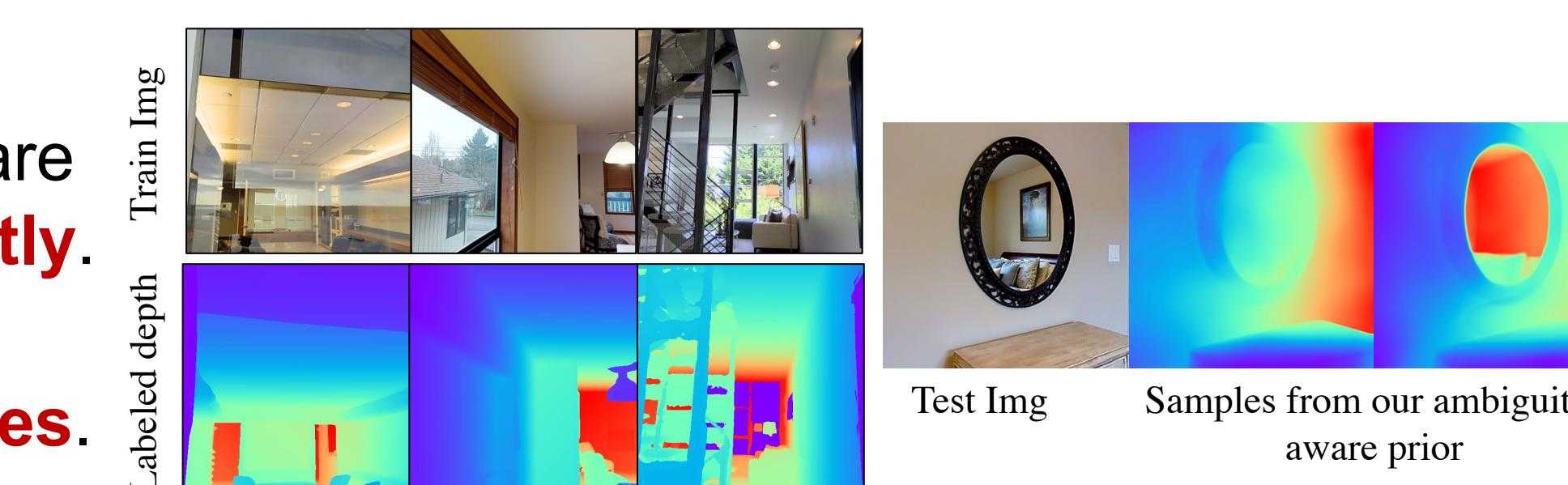
OUR AMBIGUITY-AWARE DEPTH ESTIMATES

- We represent ambiguities and capture **variable modes** through **samples** from our ambiguity-aware prior.



Why does it work?

- Training images are **labelled differently**.
- Also works on **reflective surfaces**.



RESULTS

In-the-Wild



Scannet



Ablation

	PSNR ↑	SSIM ↑	LPIPS ↓
MonoSDF supervision	20.13	0.710	0.332
DDP prior - single sample	20.85	0.712	0.320
DDP prior - multiple samples	21.00	0.718	0.316
Our prior - single sample	21.22	0.714	0.318
SCADE (Ours)	21.54	0.732	0.292

References: [1] Learning to Recover 3D shape from a Single Image. W. Yin, et. al., CVPR 2021.
[2] Multimodal Image Synthesis with Conditional Implicit Maximum Likelihood Estimation. K. Li, et. al., IJCV 2020.
[3] A Theory of Shape by Space Carving. K. Kutulakos and S. Seitz, IJCV 2000.

