Conditional-Flow NeRF: Accurate 3D Modelling with Reliable Uncertainty Quantification

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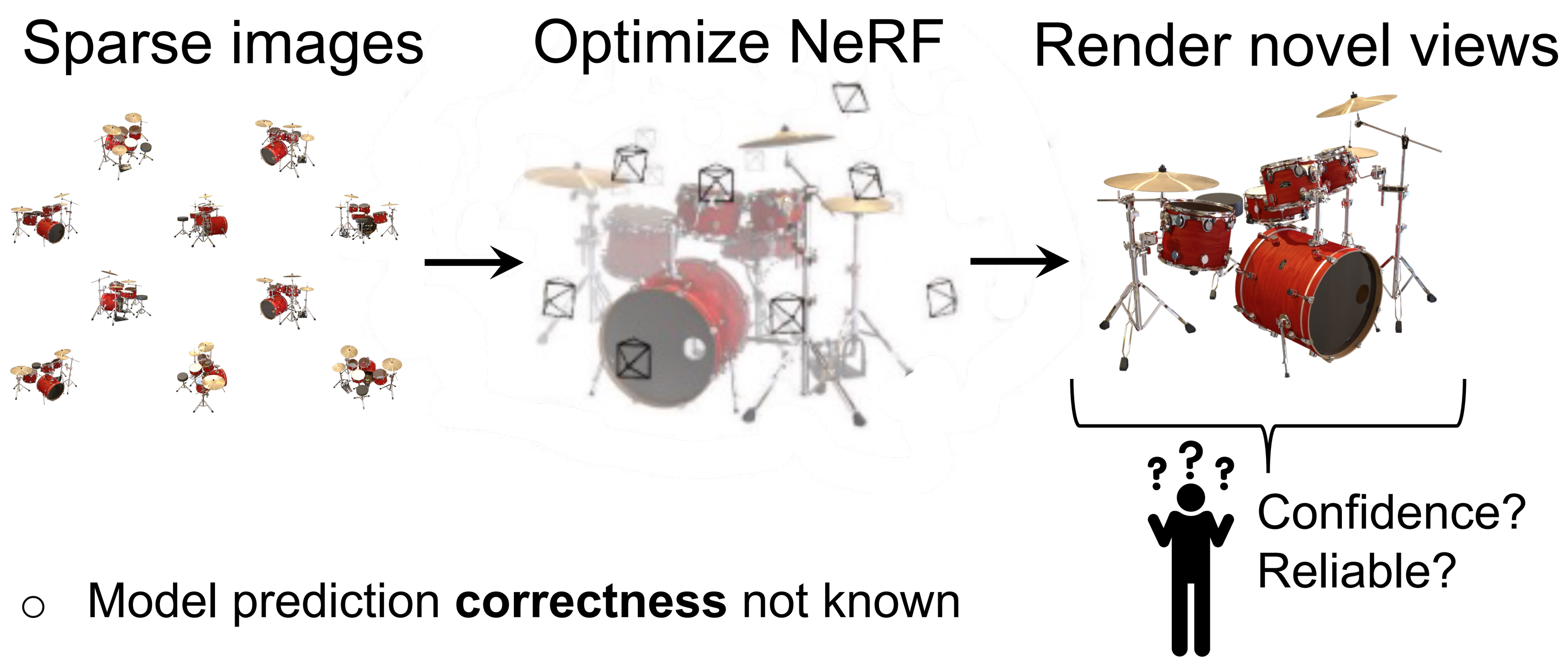
SCAN ME
ECCV TEL AVIV 2022

Introduction

Limitation of Neural Radiance Fields (NeRF)



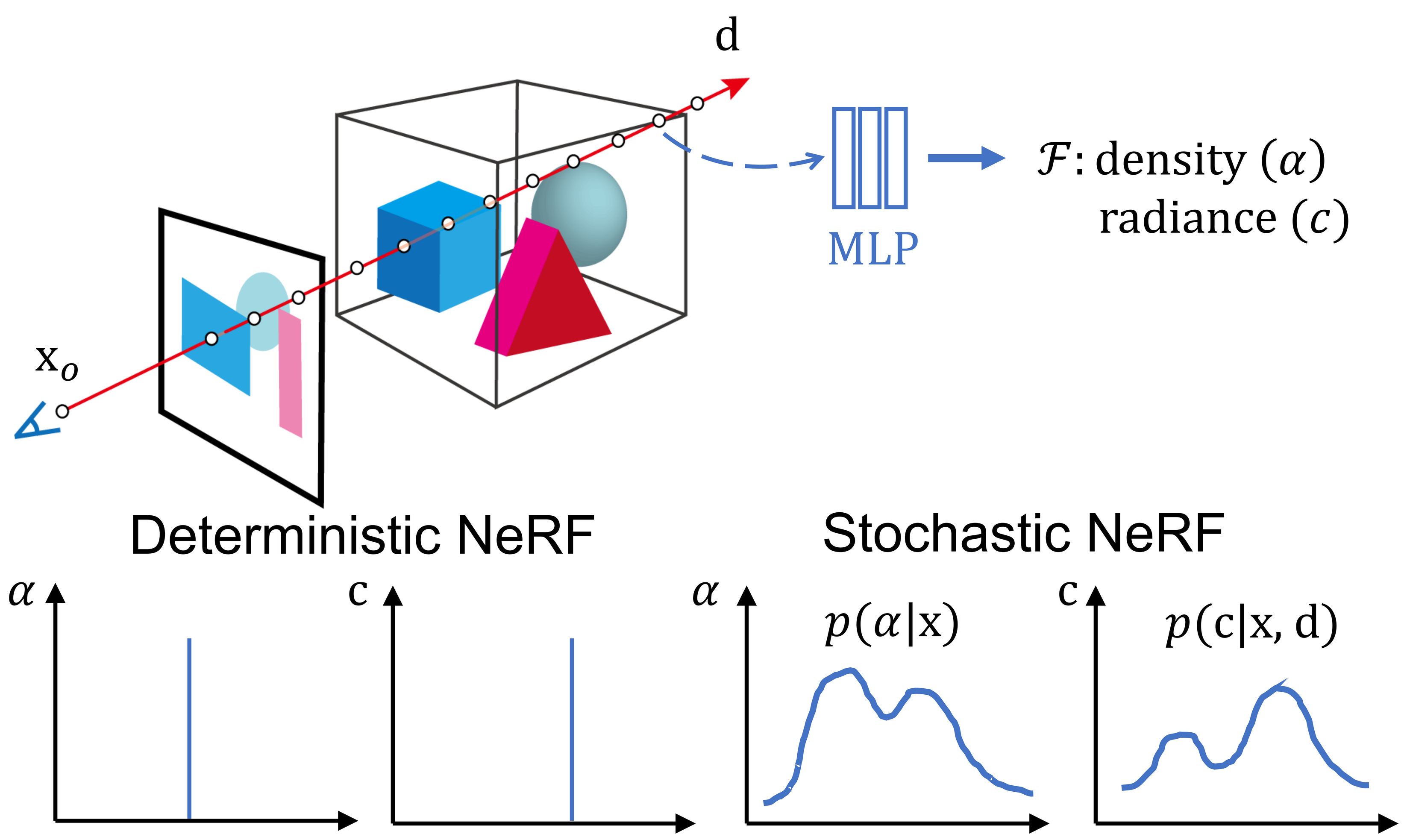
- Model prediction **correctness** not known
- No **confidence** associated with the model outputs
- Could make **Risky** decisions based on the predictions

General Uncertainty Method

	Uncertainty	Models	Forward pass	Complexity	Explicit distribution
NeRF		1	1	O(1)	
Deep Ensembles	✓	N	N	O(N²)	
MC-Dropout	✓	1	N	O(N)	
Ours	✓	1	1	O(1)	✓

- General uncertainty methods are **computationally expensive**
- Ours model an **explicit distribution** over all possible radiance fields

Deterministic VS. Stochastic NeRF

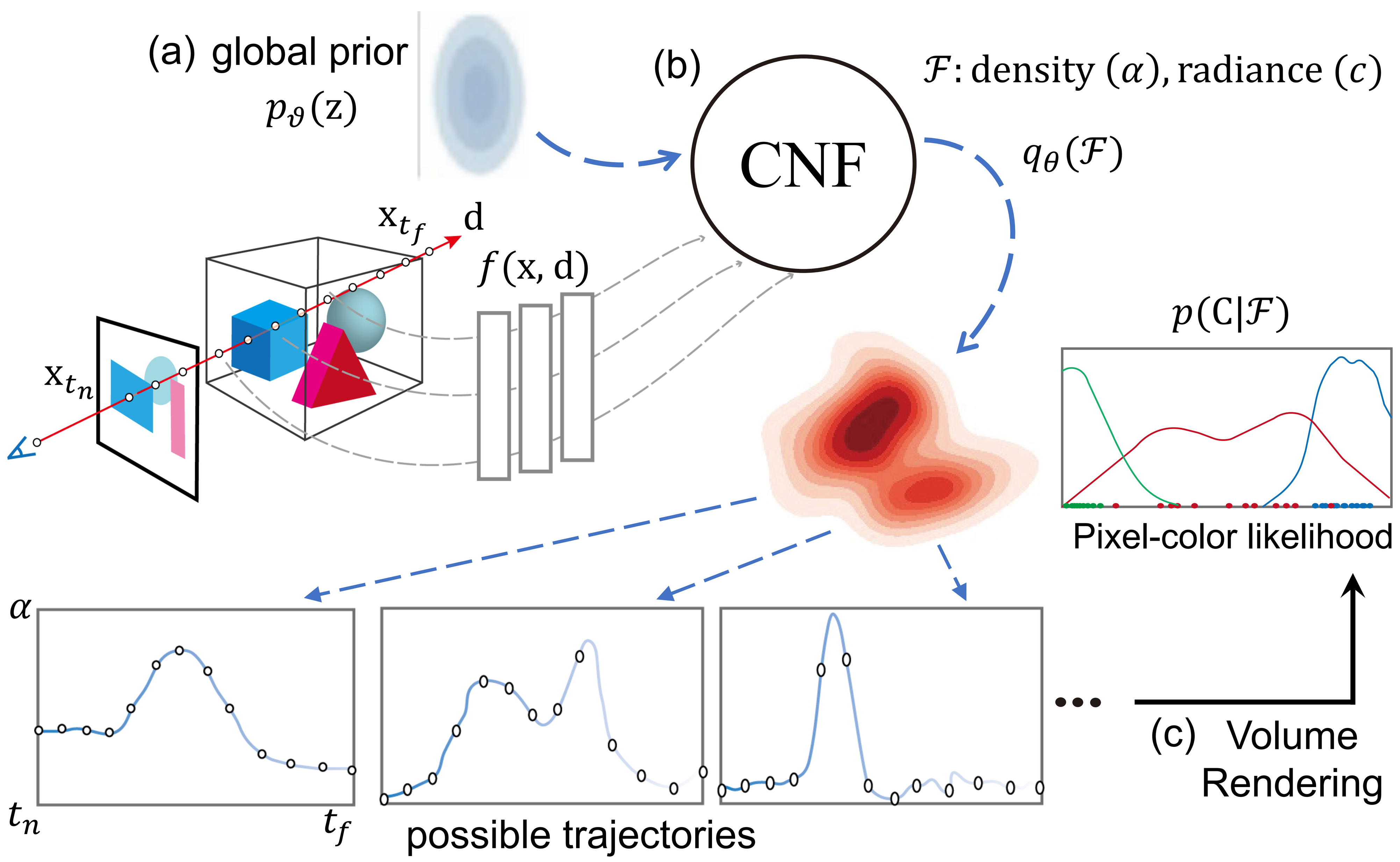


- We introduce **stochasticity** in NeRF for explicitly modelling uncertainty

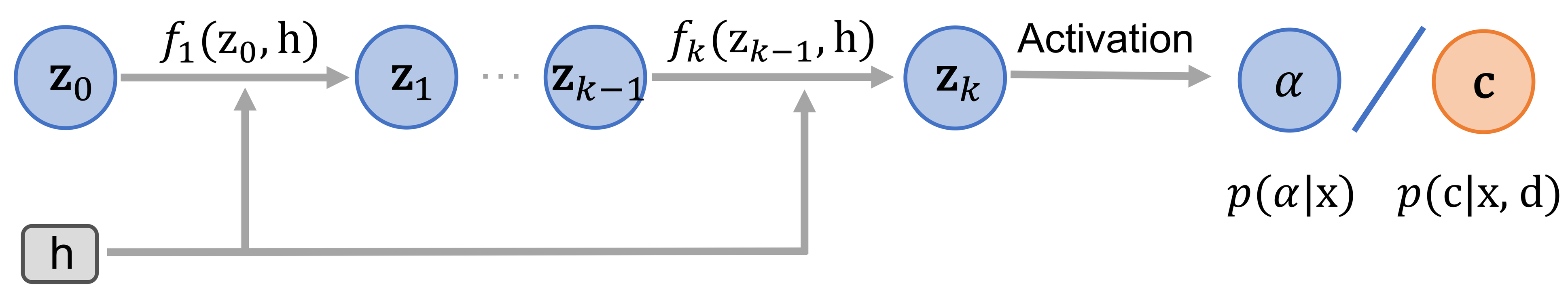
Methodology

Overall framework

(a) Latent variable modelling to introduce dependence among all 3D location
(b) Complex distribution modelling by **Conditional Normalizing Flow** (CNF)
(c) Volume Rendering to build a likelihood for pixel color



Conditional Flow



Variational Bayesian optimization

KL-divergence:

$$\min_\theta \mathbb{KL}\left(q_\theta(\mathcal{F})||p(\mathcal{F}|\mathrm{C})\right) \propto \min_\theta \underbrace{-\mathbb{E}_{q_\theta(\mathcal{F})} \log p(\mathrm{C}|\mathcal{F})}_{\text{log-likelihood (NLL)}} + \underbrace{E_{q_\theta(\mathcal{F})} \log q_\theta(\mathcal{F})}_{\text{Entropy term}}$$

Kernel density estimator (KDE):

$$\mathcal{L}_{\mathrm{NLL}} = \frac{1}{N}\sum_{n=1}^{N} \log p\left(\mathrm{C}_n|\mathcal{F}\right) \triangleq \frac{1}{N}\sum_{n=1}^{N} \log \frac{1}{K}\sum_{k=1}^{K} K_{\mathrm{H}}(\mathrm{C}_n - C_{nk})$$

Gaussian kernel

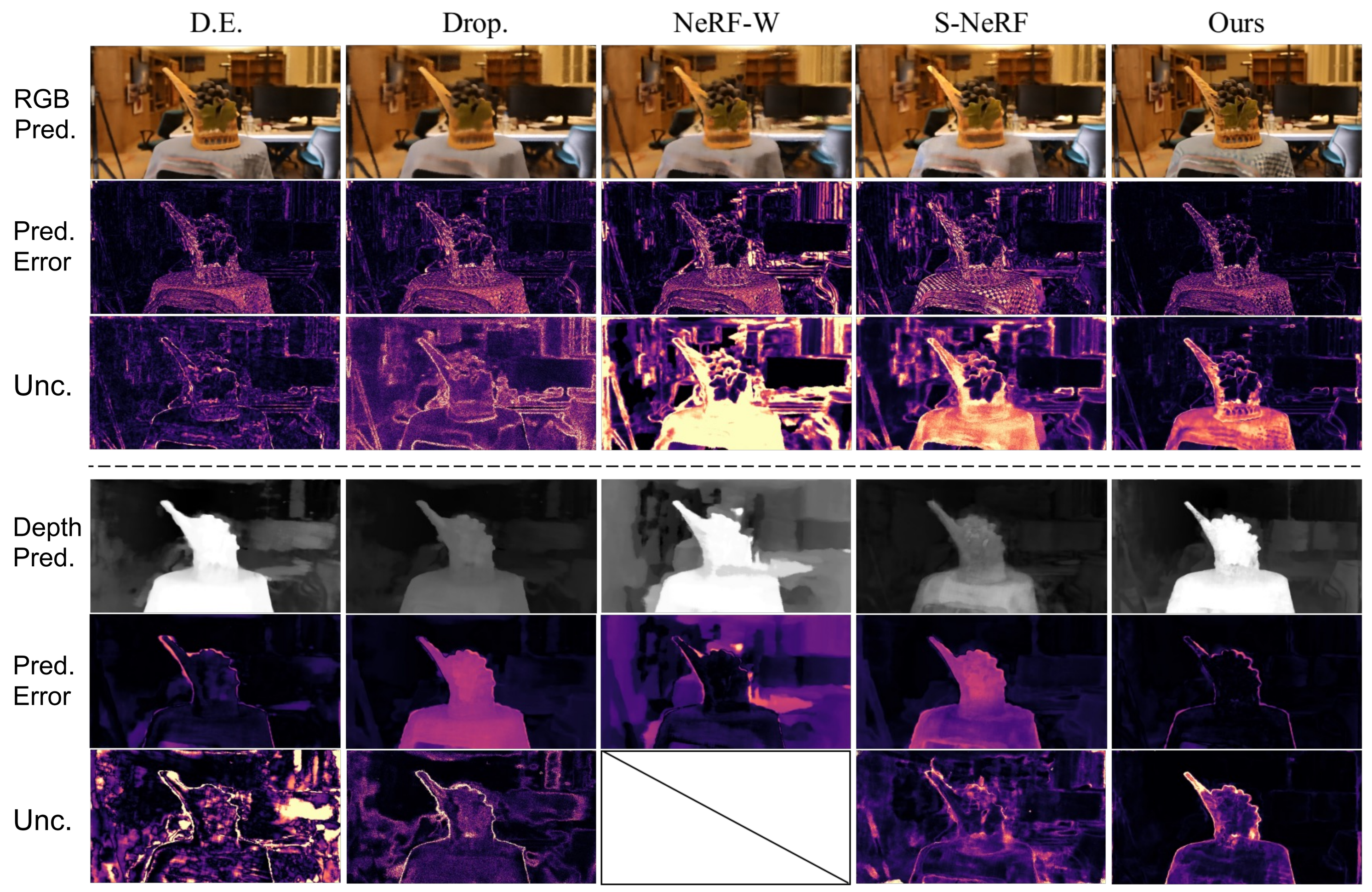
Results

Metrics

NLL: negative log-likelihood
δ_3: δ-threshold method to assess the depth quality
AUSE: uncertainty evaluation by sparsification curves

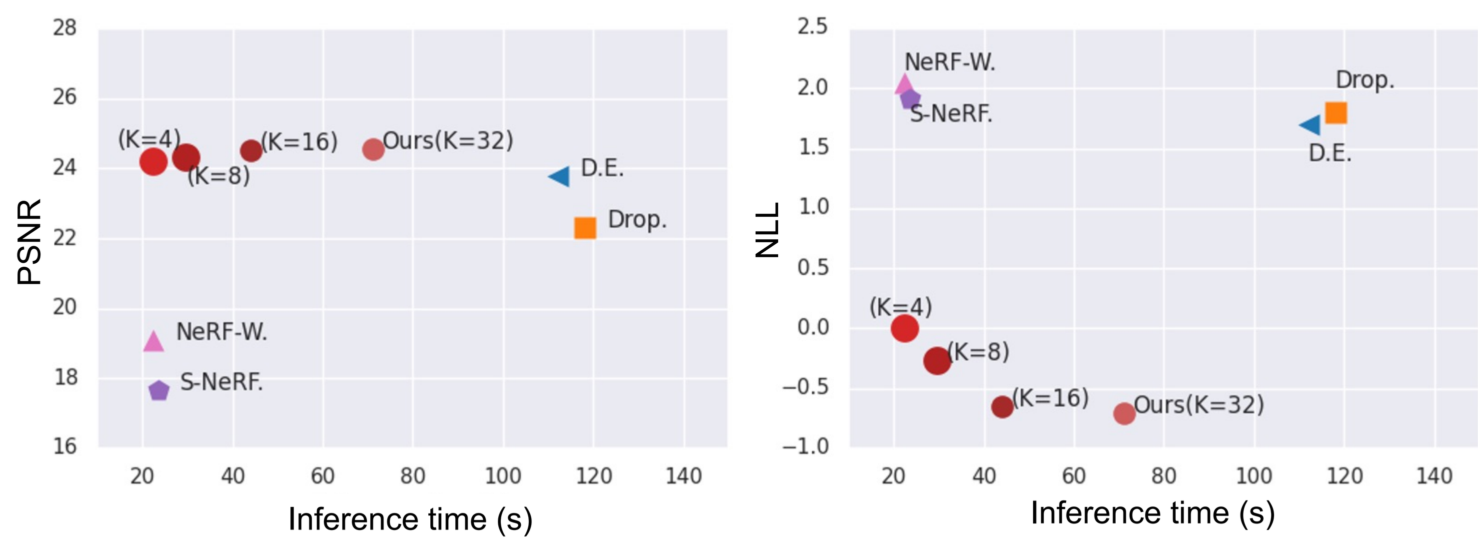
Uncertainty estimation on RGB and depth

Methods	RGB						Depth					
	Quality Metrics			Uncertainty Metrics			Quality Metrics			Uncertainty Metrics		
	PSNR	SSIM	LPIPS	AUSE RMSE	AUSE MAE	NLL	RMSE	MAE	δ_3	AUSE RMSE	AUSE MAE	NLL
D.E.	23.78	0.808	0.283	0.263	0.195	1.70	0.150	0.090	0.750	0.260	0.132	5.76
Drop.	22.32	0.740	0.398	0.311	0.253	1.81	0.229	0.149	0.348	0.497	0.395	10.21
NeRF-W	19.11	0.683	0.458	0.171	0.113	2.05	0.222	0.179	0.475	-	-	-
S-NeRF	17.69	0.603	0.548	0.271	0.355	1.92	0.420	0.375	0.248	0.416	0.490	9.38
CF-NeRF	**24.68**	**0.863**	**0.168**	**0.051**	**0.026**	**-0.71**	**0.118**	**0.074**	**0.810**	**0.110**	**0.071**	**5.09**



- Ours render visually more intuitive uncertainty maps highly correlated with the prediction error both on RGB and depth, as well as more accurate predictions

Time performance



- Ours perform the best both on image quality (PSNR) and uncertainty estimation (NLL) with a reasonable inference time
- Moreover, properly selecting the number of samples (K=8~16) reduces the inference time with a negligible impact on performance
- To further reduce time usage, our framework can be readily integrated into other efficient NeRF variants like Voxel-based instead of MLP