Team 2
Paper Presentation

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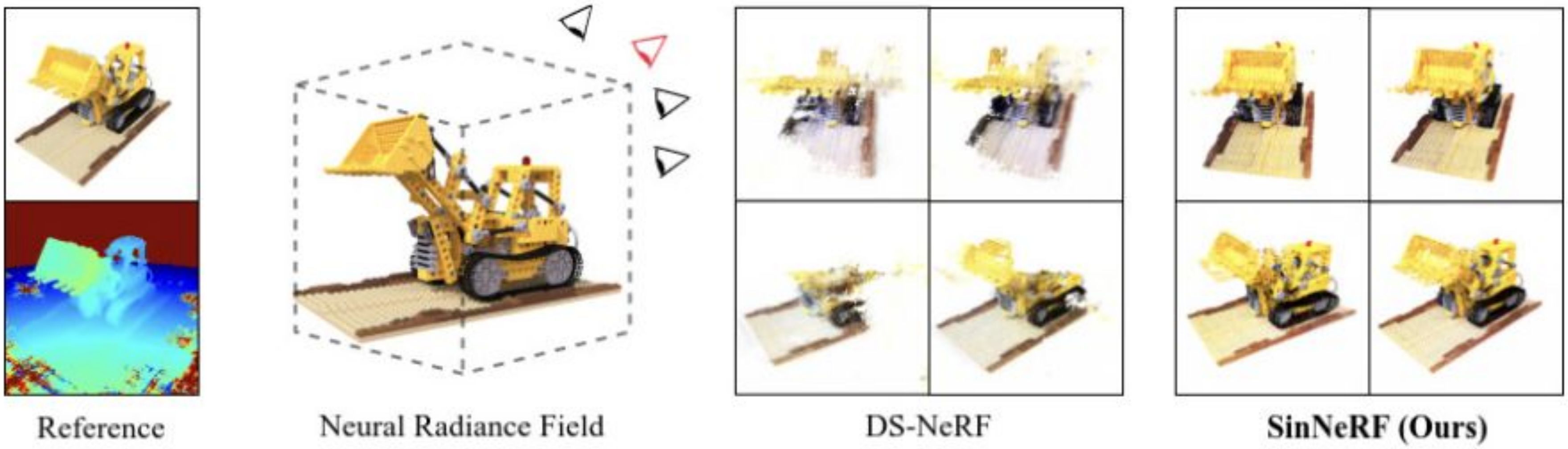
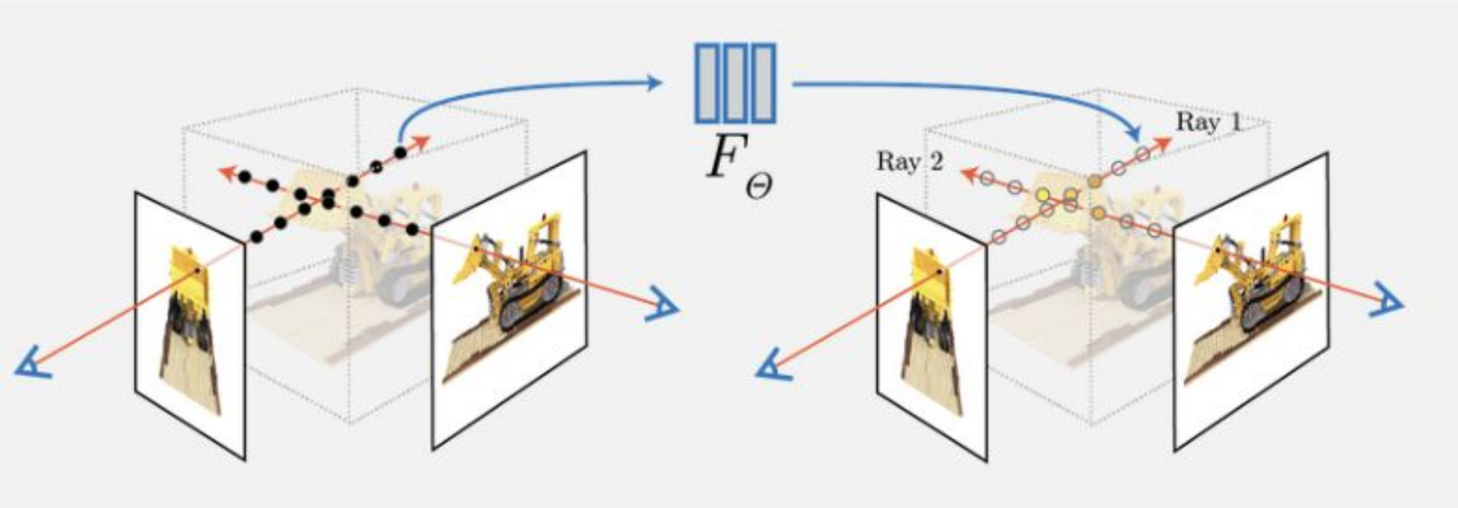
SinNeRF: Training Neural Radiance Fields from a Single Image (ECCV 2022)

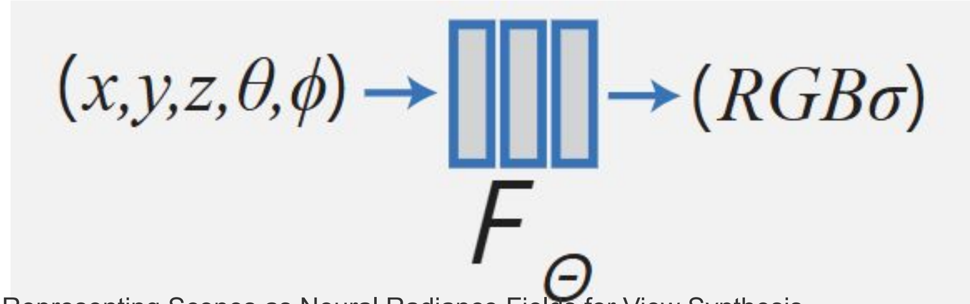


TL;DR: Given only a single reference view as input, our novel semi-supervised framework trains a neural radiance field effectively. In contrast, previous method shows inconsistent geometry when synthesizing novel views.

Dejia Xu, et al. 2022, SinNeRF: Training Neural Radiance Fields on Complex Scenes from a Single Image

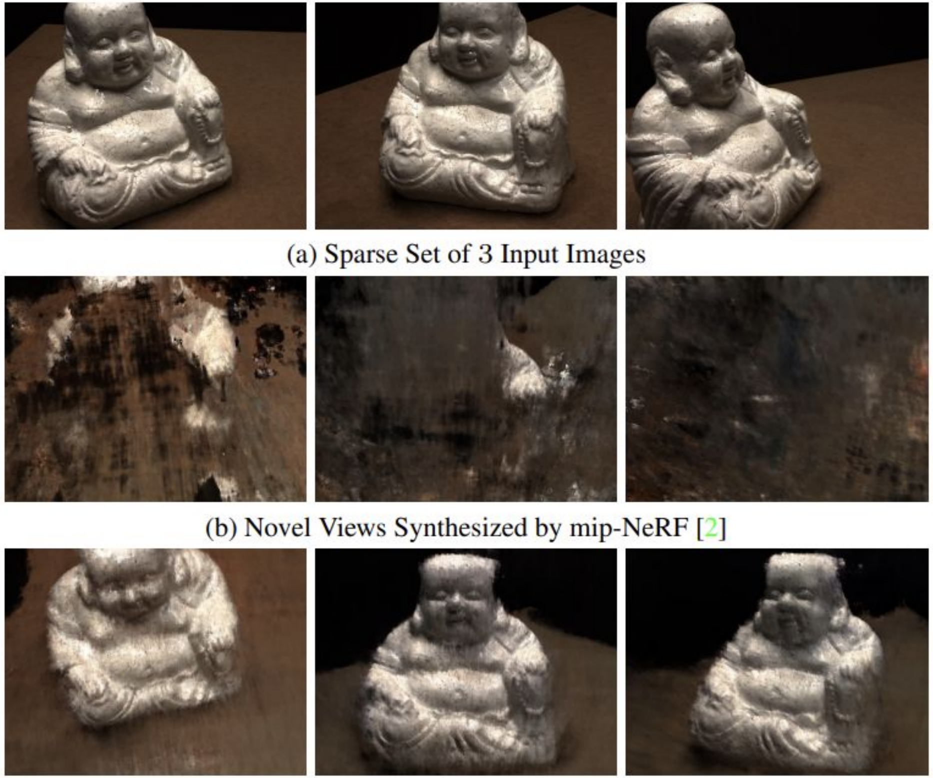
NeRF (Neural Radiance Fields)





Ben Mildenhall. et al, 2020, NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

Sparse inputs cause problems!!



(a) Sparse Set of 3 Input Images

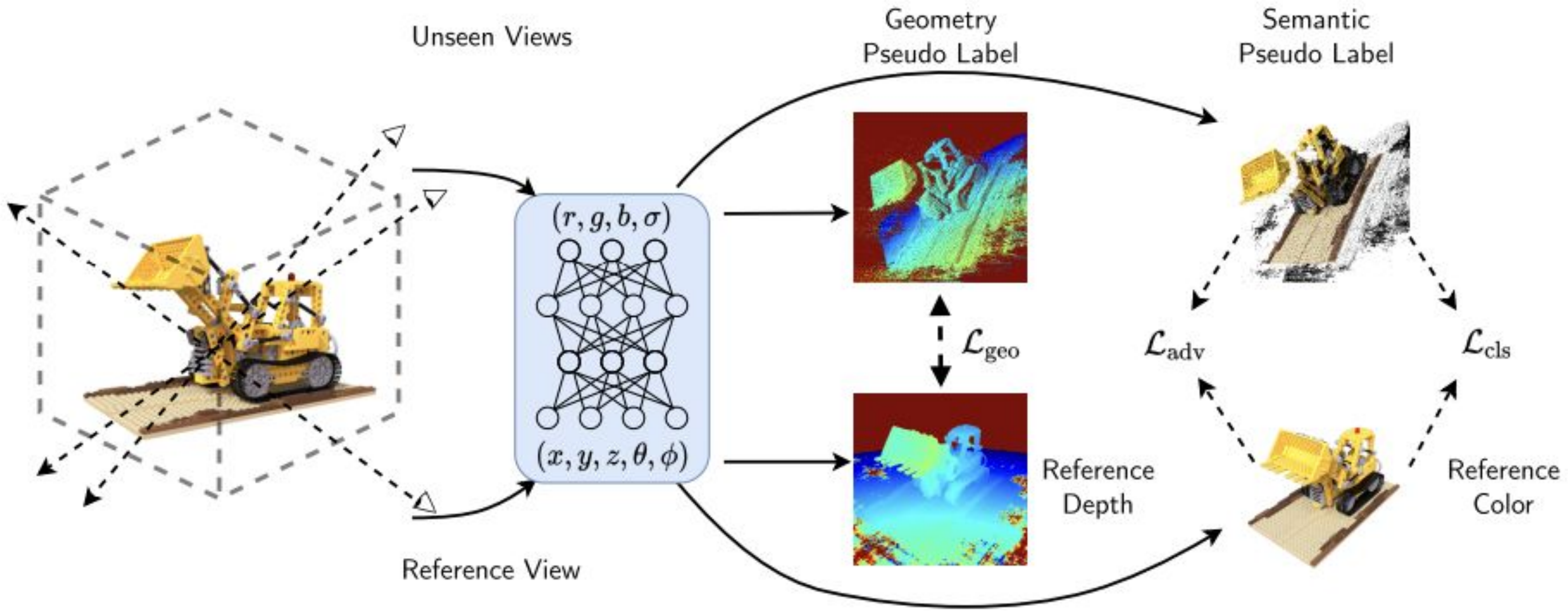
(b) Novel Views Synthesized by mip-NeRF [2]

(c) Same Novel Views Synthesized by Our Method

Michael Niemeyer. et al, 2022, RegNeRF:Regularizing Neural Radiance Fields for View Synthesis from Sparse Inputs

Solution:

Provide necessary constraints on unseen views

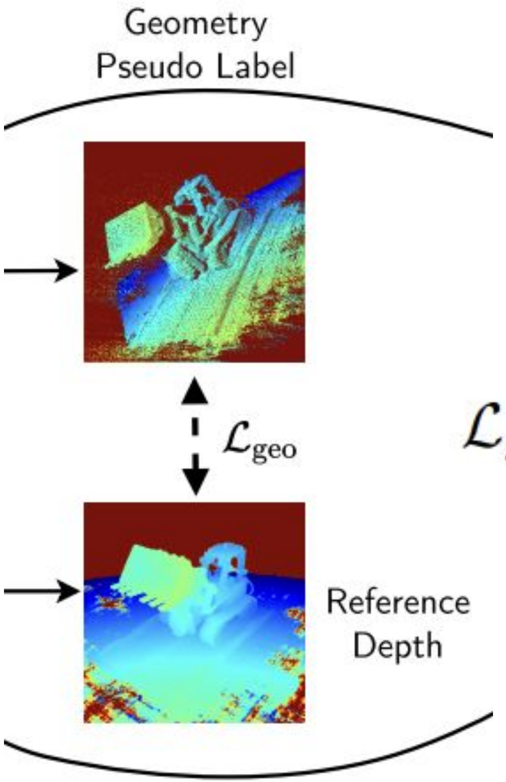


Geometry Pseudo Label (Pseudo Depth Label)

Image warping

<u>Pseudo depth label</u> is acquired during this process

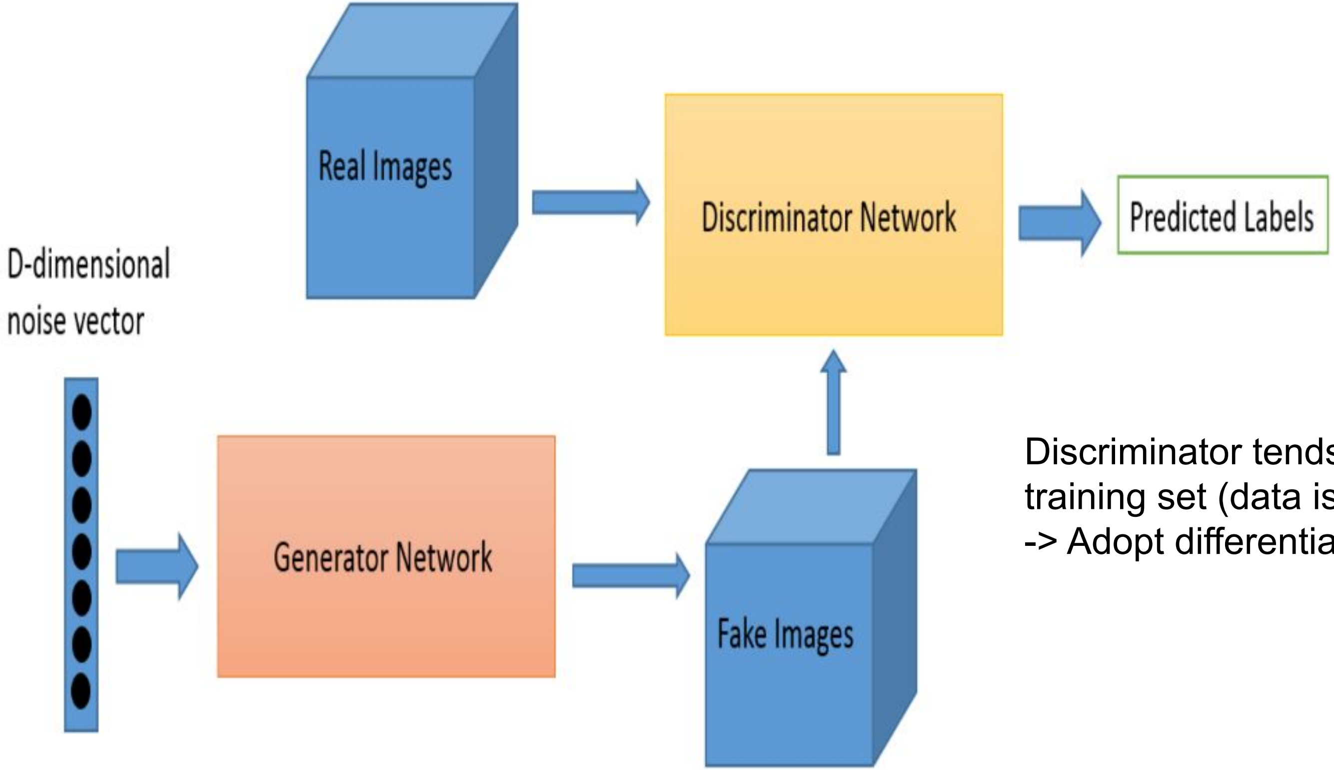
Geometry Pseudo Label



Geometric consistency with reference view and unseen view

$$\mathcal{L}_{\text{geo}} = \underbrace{\mathcal{L}_1(d_1, f(d_2))}_{\substack{\text{Depth of reference view} \\ \text{Vs} \\ \text{Depth of Image warping} \\ \text{on unseen view}}} + \underbrace{\mathcal{L}_1(f(d_1), d_2)}_{\substack{\text{Depth of unseen view} \\ \text{Vs} \\ \text{Depth of Image warping} \\ \text{on reference view}}} + \underbrace{\lambda_4 \mathcal{L}_{\text{smooth}}}_{\substack{\text{Regularize} \\ \text{uncertain regions} \\ \text{in warped results}}}$$

Semantic Pseudo Label - Local Texture Guidance



Discriminator tends to memorize entire training set (data is too limited)
-> Adopt differentiable augmentation!

Hamed Alqahtani. 2019. An Analysis Of Evaluation Metric Of GANs

Semantic Pseudo Label - Local Texture Guidance

Loss of Discriminator

$$\mathcal{L}_{\mathrm{D}} = \mathbb{E}_{\boldsymbol{x}\sim p_{\mathrm{data}}(\boldsymbol{x})}\left[f_D(-D(T(\boldsymbol{x})))\right] + \mathbb{E}_{\boldsymbol{z}\sim p(\boldsymbol{z})}\left[f_D(D(T(G(\boldsymbol{z}))))\right],$$

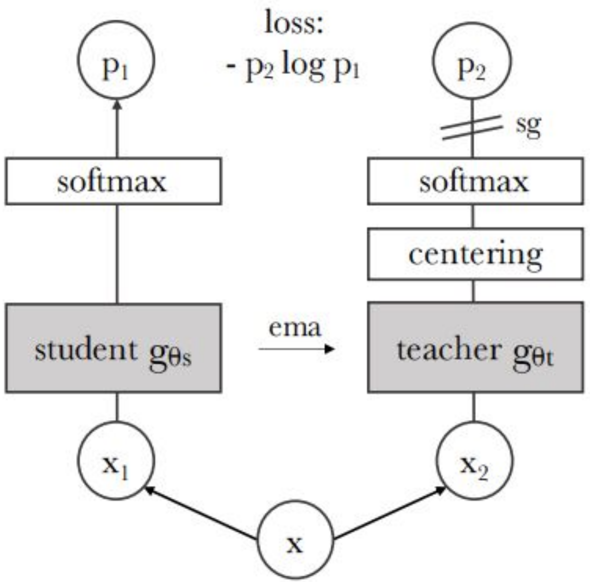
$$\mathcal{L}_{\mathrm{G}} = \mathbb{E}_{\boldsymbol{z}\sim p(\boldsymbol{z})}\left[f_G(-D(T(G(\boldsymbol{z}))))\right],$$

$$\mathcal{L}_{\mathrm{adv}} = \mathcal{L}_{\mathrm{D}} + \mathcal{L}_{\mathrm{G}},$$

Loss of Generator

Local textures are now similar between reference and unseen views

Semantic Pseudo Label - Global Texture Guidance



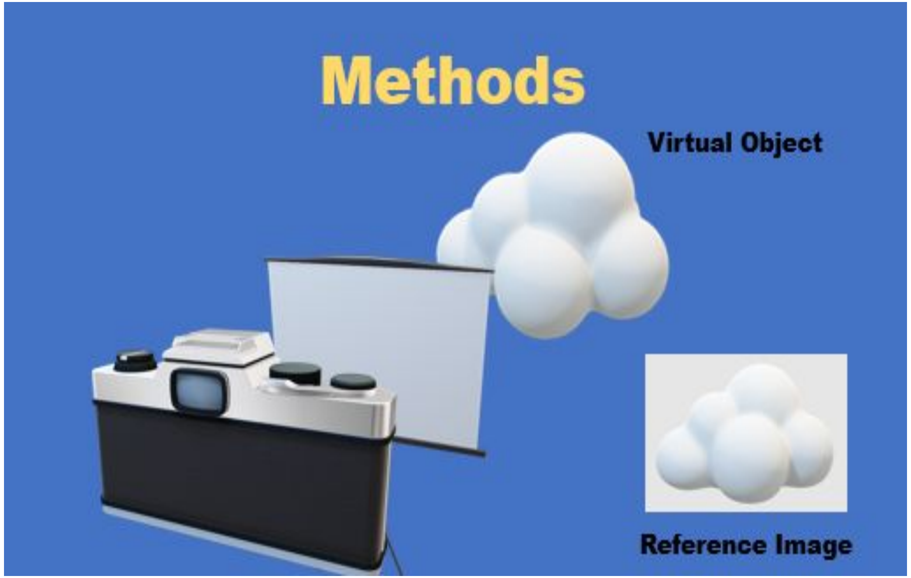
$$\mathcal{L}_{\text{cls}} = ||f_{\text{vit}}(A) - f_{\text{vit}}(B)||^2$$

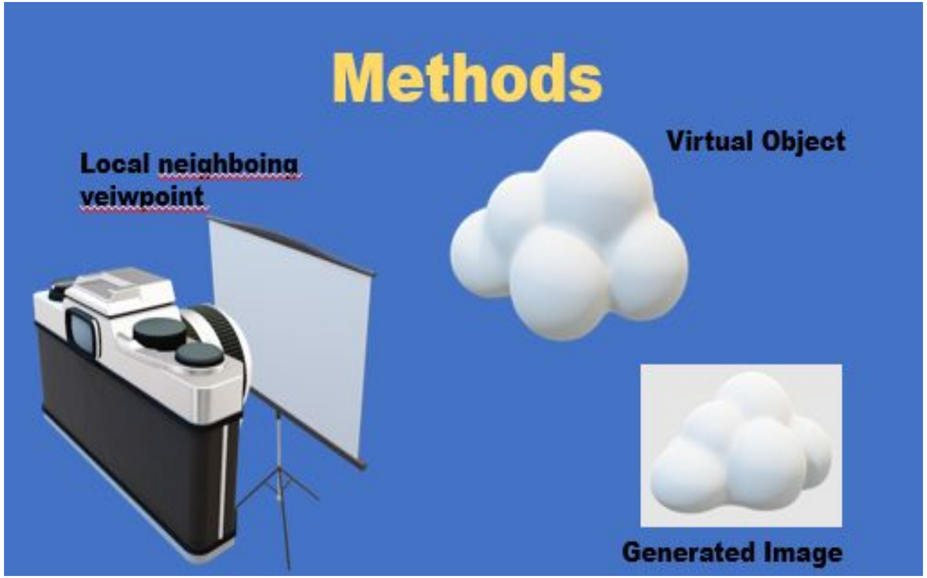
Global Texture is now similar between reference and unseen view

DINO-ViT: self supervised vision transformer
CLS tokens from DINO-ViT's output = representation of entire image

Mathilde Caron, 2021, Emerging Properties in Self-Supervised Vision Transformers

Progressive Gaussion Pose Sampling





Progressive Sampling allows network to focus on dealing with confident regions

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{pix}} + \lambda_1 \mathcal{L}_{\text{geo}} + \lambda_2 \mathcal{L}_{\text{adv}} + \lambda_3 \mathcal{L}_{\text{cls}},$$

Quantitative evaluations

Scene	Pose Error					
	Translation($\times 10^{-2}$) $\downarrow$			Rotation($^\circ$) $\downarrow$		
	NeRFmm128	*NeRFmm256*	**SiNeRF**	*NeRFmm128*	*NeRFmm256*	**SiNeRF**
Fern	0.514	0.765	**0.438**	0.957	1.566	**0.743**
Flower	1.039	1.200	**0.796**	3.657	3.211	**0.506**
Fortress	6.463	6.046	**4.068**	2.590	2.410	**1.772**
Horns	1.607	**1.476**	2.153	3.806	3.044	**2.662**
Leaves	0.676	**0.608**	0.831	8.248	**6.782**	8.762
Orchids	1.627	2.243	**1.257**	4.140	5.459	**3.244**
Room	**1.315**	2.148	2.145	3.357	3.745	**2.075**
Trex	1.213	1.467	**0.462**	4.953	6.339	**0.856**
Mean	1.807	1.994	**1.519**	3.964	4.070	**2.578**

Scene	Image Quality								
	PSNR $\uparrow$			SSIM $\uparrow$			LPIPS $\downarrow$		
	NeRFmm128	*NeRFmm256*	**SiNeRF**	*NeRFmm128*	*NeRFmm256*	**SiNeRF**	*NeRFmm128*	*NeRFmm256*	**SiNeRF**
Fern	21.811	22.154	**22.482**	0.631	0.648	**0.665**	0.479	0.459	**0.437**
Flower	25.430	26.606	**27.229**	0.714	0.772	**0.798**	0.366	0.296	**0.295**
Fortress	26.173	25.596	**27.465**	0.653	0.602	**0.722**	0.438	0.538	**0.393**
Horns	22.949	23.174	**24.142**	0.626	0.635	**0.684**	0.492	0.506	**0.431**
Leaves	18.647	**19.741**	19.152	0.512	**0.609**	0.571	0.476	**0.385**	0.392
Orchids	16.695	15.858	**16.922**	0.391	0.350	**0.408**	0.540	0.550	**0.529**
Room	25.623	25.675	**26.101**	0.831	0.836	**0.844**	0.450	**0.411**	0.426
Trex	22.551	23.376	**24.939**	0.719	0.759	**0.816**	0.438	0.390	**0.356**
Mean	22.485	22.773	**23.554**	0.635	0.651	**0.689**	0.460	0.442	**0.407**

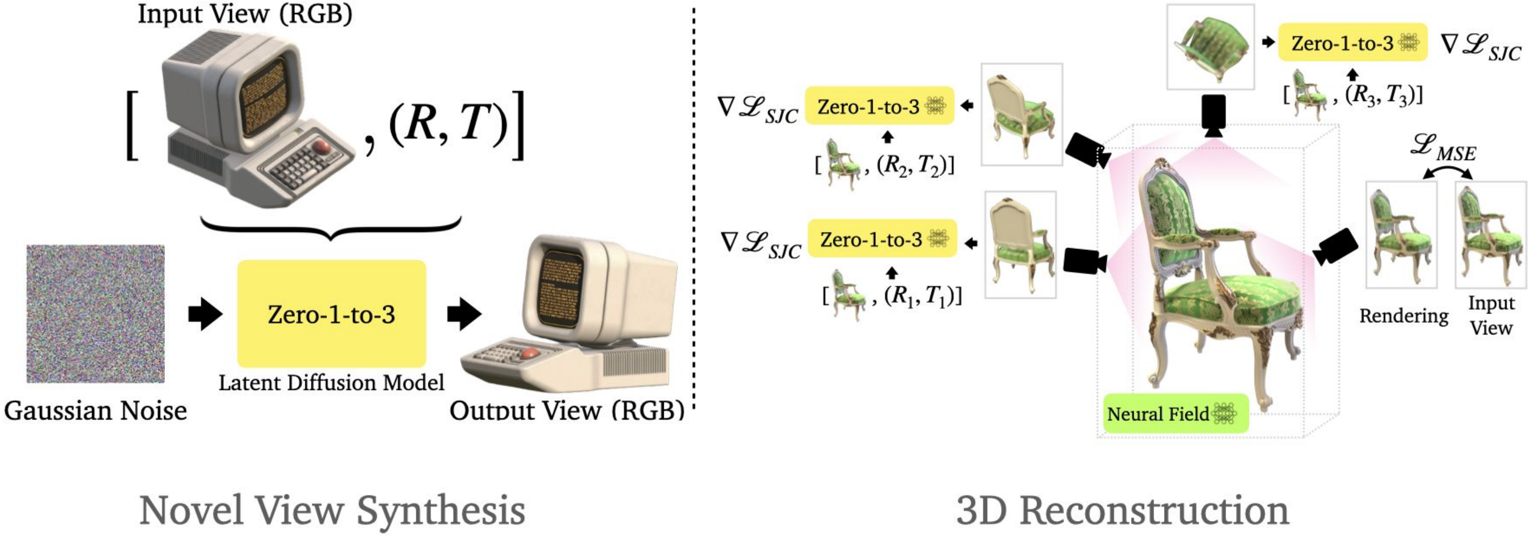
Qualitative results

Limitations

- Computational Intensity
- Generalization Constraints
- High Memory Usage
- Limited Performance in Large-Scale Scenes
- Potential Overfitting

Zero-1-to-3: Zero-shot One Image to 3D Object (ICCV 2023)

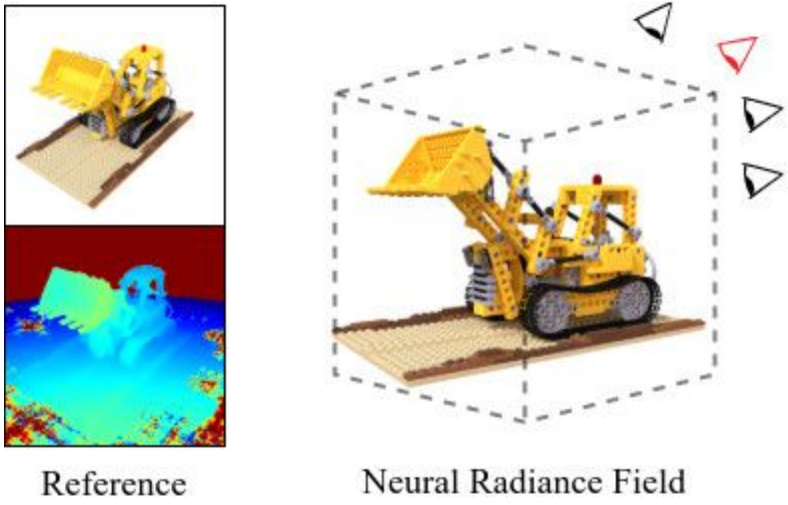
Ruoshi Liu — Columbia University
Rundi Wu — Columbia University
Basile Van Hoorick — Columbia University
Pavel Tokmakov — Toyota Research Institute
Sergey Zakharov — Toyota Research Institute
Carl Vondrick — Columbia University



Liu, Ruoshi, et al. "Zero-1-to-3: Zero-shot one image to 3d object." Proceedings of the IEEE/CVF international conference on computer vision. 2023.

Leveraging Stronger Priors

Pure NeRF/3DGS approaches are **ill-posed**



Not Enough Information!
(Ambiguities about Novel Views)

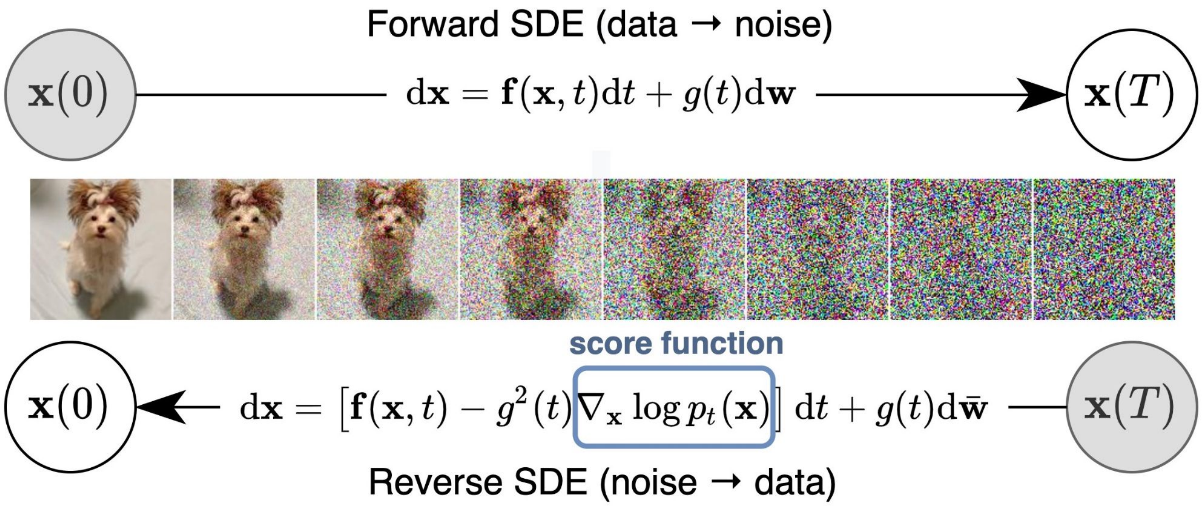
Solution:

Leverage Stronger Priors from Training Data

Objaverse-XL
> 10 million 3D objects

Deitke, Matt, et al. "Objaverse-xl: A universe of 10m+ 3d objects." Advances in Neural Information Processing Systems 36 (2024).

Diffusion Models



Key Idea:

$\underbrace{\textbf{Reverse Noising}}_{\textbf{Learnable}}$ Converts $\underbrace{\textbf{Gaussian Noise}}_{\textbf{Easy to Sample}}$ into $\underbrace{\textbf{Clean Images}}_{\textbf{Hard to Sample}}$

Credit: https://yang-song.net/blog/2021/score/

Classifier Free Guidance

Given **(image, condition)** pairs, train to generate an image to match the condition

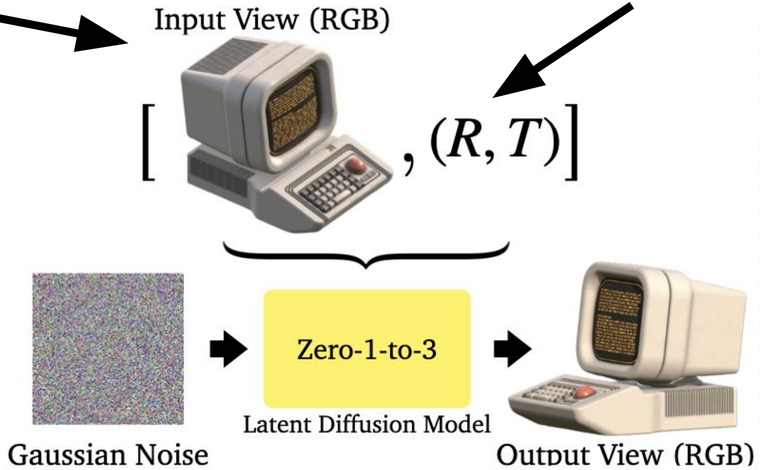
Text-to-Image

https://openai.com/index/dall-e-3/

Zero123: Conditional Diffusion Model

Reference Image

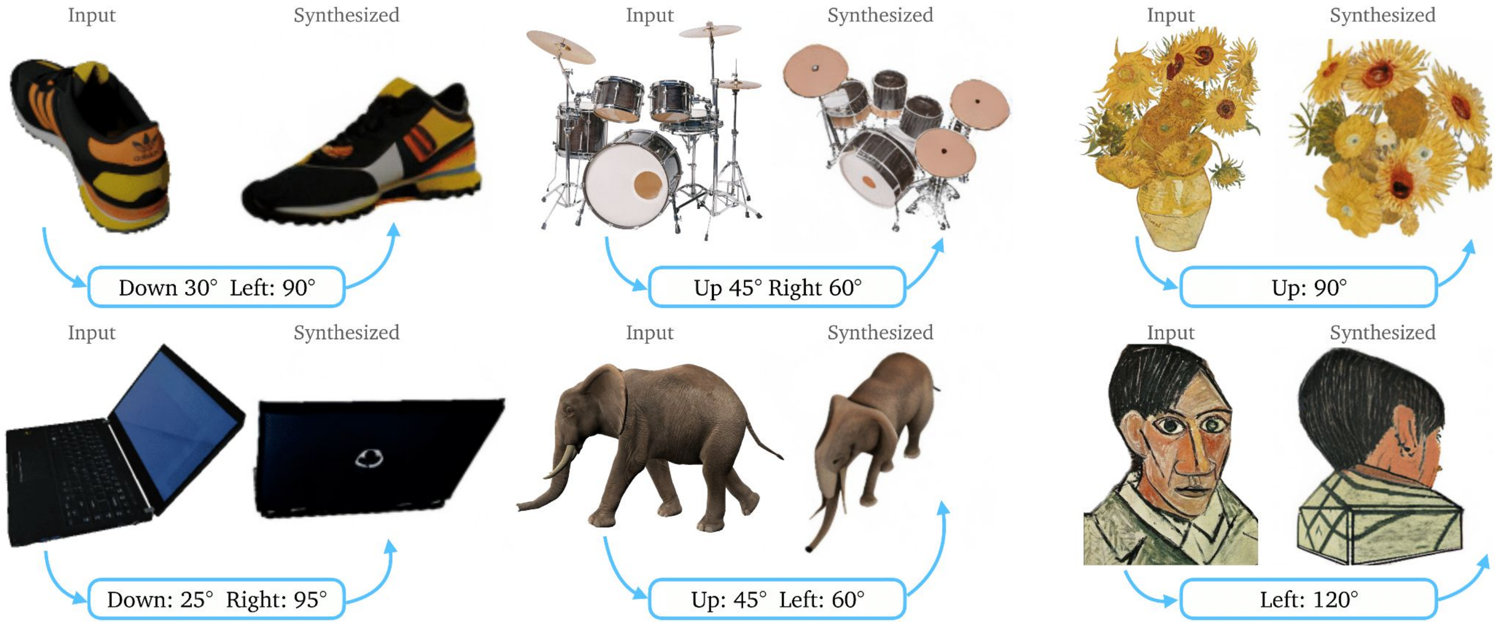
Relative Camera position and Orientation



Novel View Synthesis

Trained on Objaverse(-XL)

Single-Image Novel View Synthesis



Quantitative Results

	DietNeRF [23]	Image Variation [1]	SJC-I [53]	Ours
PSNR ↑	8.933	5.914	6.573	**18.378**
SSIM ↑	0.645	0.540	0.552	**0.877**
LPIPS ↓	0.412	0.545	0.484	**0.088**
FID ↓	12.919	22.533	19.783	**0.027**

Google Scanned Objects Dataset (Single-Object)

	DietNeRF [23]	Image Variation [1]	SJC-I [53]	Ours
PSNR ↑	7.130	6.561	7.953	**10.405**
SSIM ↑	0.406	0.442	0.456	**0.606**
LPIPS ↓	0.507	0.564	0.545	**0.323**
FID ↓	5.143	10.218	10.202	**0.319**

RTMV (Multi-Object)

Discussion

Pros

- By using training data, captures richer priors
- SoTA performance
- “Training-free” – No need to retrain for each object

Cons

- Only works on background-less images
- Generates random views depending on initial noise
- Slow generation speed