Generative Neural Fields by Mixtures of Neural Implicit Functions

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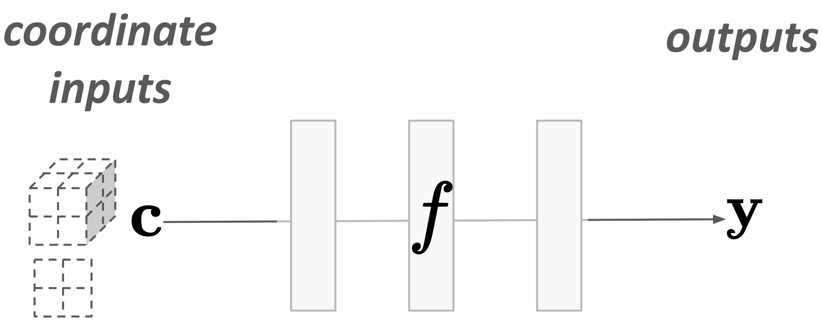
Implicit Neural Representation

- Implicit neural representations (or neural fields) represents a data using implicit function *f*.



$$\mathbf{y} = f(\mathbf{c}) = f^{(L+1)} \circ f^{(L)} \cdots \circ f^{(0)}(\mathbf{c})$$

$$\mathbf{h}^{(i+1)} = f^{(i)}(\mathbf{h}^{(i)}) = \mathrm{Act}(\mathbf{W}^{(i)}\mathbf{h}^{(i)} + \mathbf{b}^{(i)})$$

$$\mathbf{c} = \mathbf{h}^{(0)} \qquad \mathbf{y} = \mathbf{h}^{(L+2)}$$

$$\mathcal{C}(\mathbf{c}) = \sum_{(\mathbf{c}^{(i)}, y^{(i)}) \in \mathcal{D}} ||f(\mathbf{c}^{(i)}) - y^{(i)}||^2$$

Image

$$(c_x, c_y) \mapsto (y_R, y_G, y_B)$$

Voxel

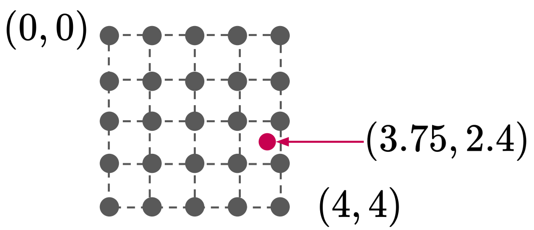
$$(c_x, c_y, c_z) \mapsto (y_\sigma)$$

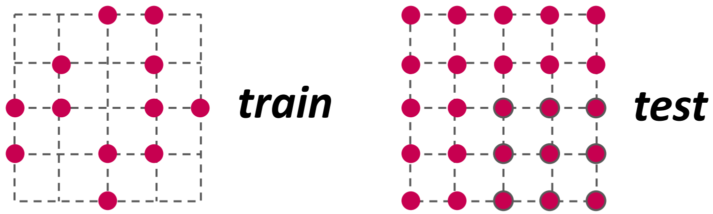
Radiance Fields

$$(c_x, c_y, c_z, c_\theta, c_\phi) \mapsto (y_R, y_G, y_B, y_\sigma)$$

Merits of INR

- Input coordinate queries on continuous grids
  - Input coordinate queries are independent each other.





- Compression ability
  - *"Our method [NeRF] requires only 5 MB for the network weights, which is even less memory than the input images alone for a single scene from any of our datasets."*
  - Neural Representation for Video [NeRV] compresses a video comparable to off-the-shelf video codecs, such as H.264.

[NeRF] Ben Mildenhall, et al., **Representing Scenes as Neural Radiance Fields for View Synthesis**, ECCV 2020
[NeRV] Hao Chen, et al., **NeRV: Neural Representations for Videos**, NeurIPS 2021

Limitation of INR

- Only memorizing a single object or scene

A single NeRF scene

- Generation 3D scene is tricky due to a large parameter space

→ Motivation for generative mechanism for INR or neural fields

[Gaussian Splatting] 3D Gaussian Splatting for Real-Time Radiance Field Rendering, SIGGRAPH 2023

Motivation

- Model Averaging for Implicit Neural Representation
    - Simple conditioning mechanism for INR
    - Increasing capacity of generative neural fields without additional inference costs

Mixtures of INR weights within parameter space
for compact generative neural fields

Ensemble of Model Weights

- Ensembling weights within parameter space
  - Several evidences from distinct tasks and architectures, such as domain generalization [SWA], generative model [EMA-GAN] and generic transfer learning [ModelSoup]
  - No requirement for additional inference cost

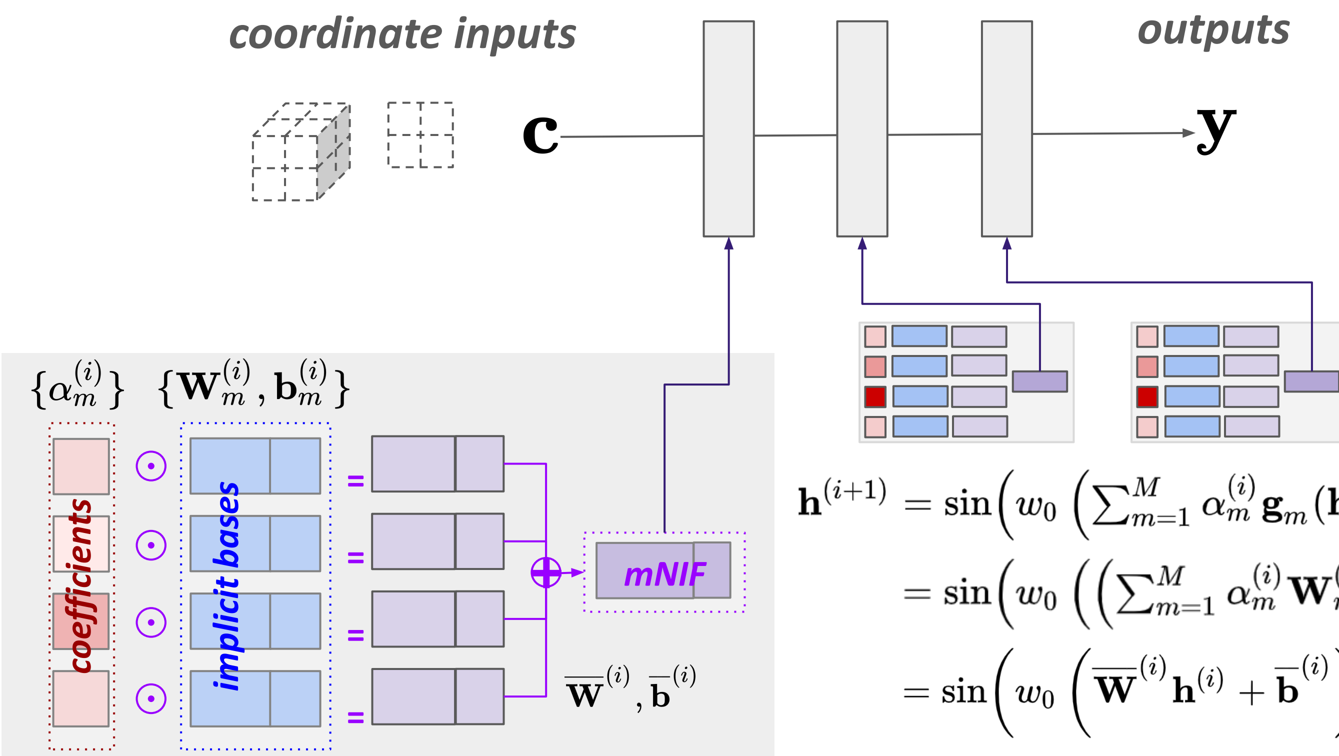
$$\mathbf{y} = f(\mathbf{x}; \boldsymbol{\theta}) \quad \Longrightarrow \quad \mathbf{y} = f(\mathbf{x}; \overline{\boldsymbol{\theta}})$$

$$\overline{\boldsymbol{\theta}} = \sum_{m=1}^{M} \alpha_m \cdot \boldsymbol{\theta}_m$$

[SWA] Pavel Izmailov, et al., **Averaging Weights Leads to Wider Optima and Better Generalization**, UAI 2018
[EMA-GAN] Yasin Yazıcı, et al., **The Unusual Effectiveness of Averaging in GAN Training**, ICLR 2019
[ModelSoup] Mitchell Wortsman, et al., **Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time**, ICML 2022

Mixture of Neural Implicit Functions

- Mixtures of neural implicit functions

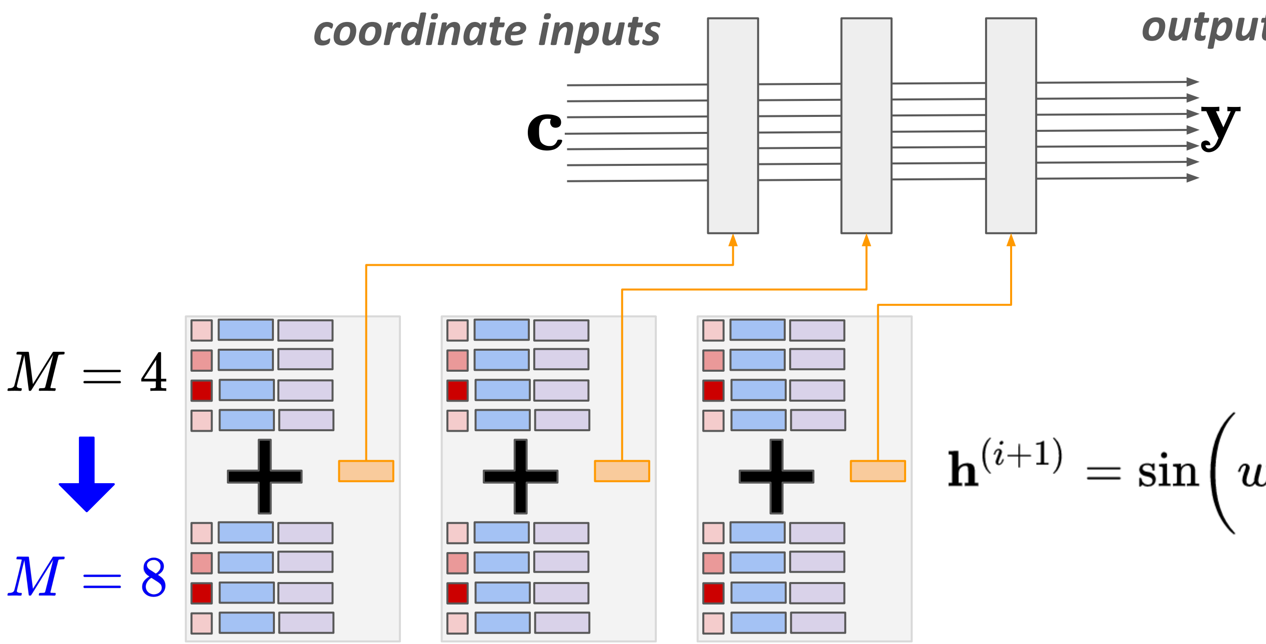


$$
\begin{aligned}
\mathbf{h}^{(i+1)} &= \sin\left(w_0 \left(\sum_{m=1}^{M} \alpha_m^{(i)} \mathbf{g}_m(\mathbf{h}^{(i)})\right)\right) \\
&= \sin\left(w_0 \left(\left(\sum_{m=1}^{M} \alpha_m^{(i)} \mathbf{W}_m^{(i)}\right) \mathbf{h}^{(i)} + \sum_{m=1}^{M} \alpha_m^{(i)} \mathbf{b}_m^{(i)}\right)\right) \\
&= \sin\left(w_0 \left(\overline{\mathbf{W}}^{(i)} \mathbf{h}^{(i)} + \overline{\mathbf{b}}^{(i)}\right)\right)
\end{aligned}
$$

$M = 4$

Merits of mNIF

- Easy to increase the capacity of generative INR
- Efficient computation for numerous coordinate queries
- Compact size of neural field instance



independent from the number of mixtures (M)

$$\mathbf{h}^{(i+1)} = \sin\left(w_0 \left(\overline{\mathbf{W}}^{(i)} \mathbf{h}^{(i)} + \overline{\mathbf{b}}^{(i)} \right) \right)$$

Benchmarks

- Unconditioned generation of Image, Voxel, Radiance Fields

Image

$(c_x, c_y) \mapsto (y_R, y_G, y_B)$

- CelebA-HQ 64^2
- Train (27,000) Test (3,000)
- Protocol from [Functa]
- Fréchet Inception Distance (FID)

Voxel

$(c_x, c_y, c_z) \mapsto (y_\sigma)$

- ShapeNet 64^3
- Train (35,019) Test (8,762)
- Protocol from [GEM]
- Coverage & Maximum Mean Discrepancy (MMD) with Chamfer distance

Radiance Fields

$(c_x, c_y, c_z) \mapsto (y_R, y_G, y_B, y_\sigma)$

- SRN Cars with 128^2 pixels
- Train (2,458) Test (704)
- Protocol from [Functa]
- Simplified NeRF rendering without ray direction (θ, ϕ)
- FID of images from pre-defined 251 views

[Functa] Emilien Dupont, et al., **From data to functa: Your data point is a function and you can treat it like one**, ICML 2022
[GEM] Yilun Du, et al., **Learning Signal-Agnostic Manifolds of Neural Fields**, NeurIPS 2021

Performance on Image

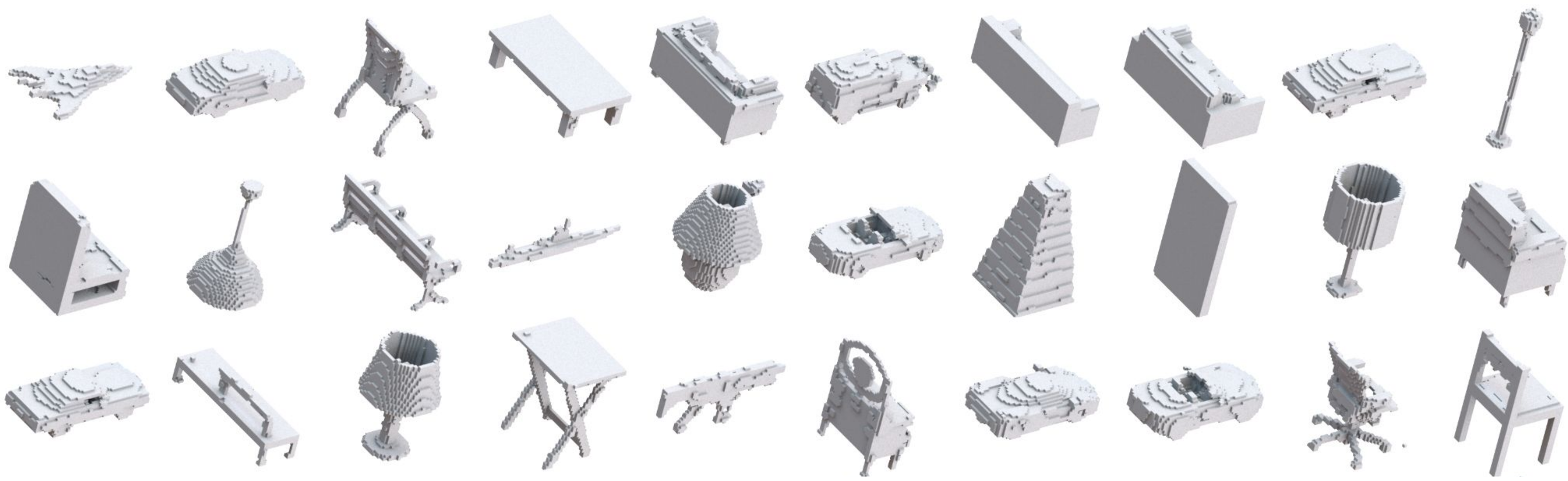
- Image generation performance on CelebA-HQ 64^2.

Model	# Params		Reconstruction (train)		Generation (train)				Efficiency	
	Learnable	Inference	PSNR ↑	rFID ↓	FID ↓	Precision ↑	Recall ↑	F1 ↑	fps	GFLOPS
Functa	3.3 M	2,629.6 K	26.6	28.4	40.4	0.577	0.397	0.470	332.9	8.602
GEM	99.0 M	921.3 K	-	-	30.4	0.642	0.502	0.563	559.6	3.299
GASP	34.2 M	83.1 K	-	-	13.5	0.836	0.312	0.454	1949.3	0.305
DPF	62.4 M	-	-	-	13.2	0.866	0.347	0.495	-	-
mNIF (S)	4.6 M	17.2 K	31.5	10.9	21.0	0.787	0.324	0.459	2958.6	0.069
mNIF (L)	33.4 M	83.3 K	34.5	5.8	13.2	0.902	0.544	0.679	891.3	0.340

Performance on Voxel

- Voxel generation performance on ShapeNet 64^3.

Model	# Params		Reconstruction (test)		Generation (test)		Inference Efficiency	
	Learnable	Inference	MSE ↓	PSNR ↑	Coverage ↑	MMD ↓	fps	GFLOPS
GASP	34.2 M	83.1 K	0.0296	16.52	0.341	0.0021	180.9	8.742
GEM	99.0 M	921.3 K	0.0153	21.32	0.409	0.0014	16.7	207.0
DPF	62.4 M	-	-	-	0.419	0.0016	-	-
mNIF (S)	4.6 M	17.2 K	0.0179	20.26	0.430	0.0014	191.5	4.363
mNIF (L)	33.4 M	83.3 K	0.0166	21.38	0.437	0.0013	69.6	21.613



Performance on Radiance Fields

- Radiance field generation performance on SRN Cars.

Model	# Params		Reconstruction (train)	Generation (test)	Inference Efficiency		
	Learnable	Inference	PSNR ↑	FID ↓	fps	TFLOPS	Memory
Functa	3.9 M	3,418.6 K	24.2	80.3	2.0	1.789	28.01 GB
mNIF (S)	4.6 M	17.2 K	25.9	79.5	97.7	0.009	1.26 GB

view 64 view 128 view 192

Interpolation of Context Vectors

Thank you for watching the video

Poster Session 3

Great Hall & Hall B1+B2 **Poster #537**

Wed 13th Dec 10:45 a.m. CST — 12:45 p.m. CST