HYPER-TRANSFORMING LATENT DIFFUSION MODELS

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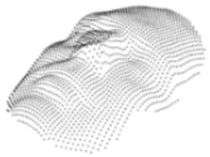
PIONEER CENTRE FOR ARTIFICIAL INTELLIGENCE

Introduction

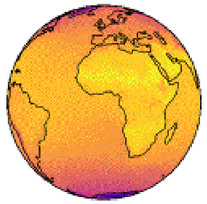
- We typically discretized data that are continuous in nature.
- Real data can be expressed as a function over continuous coordinate systems.

2D Images

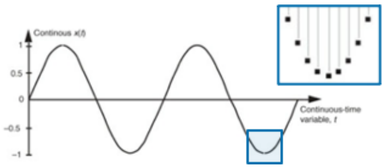
3D Images



Polar data

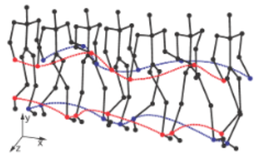


Time series

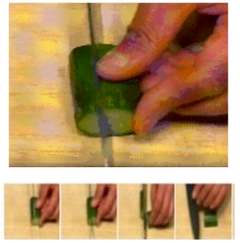


Audio

Motion sequences



Video



Spatial

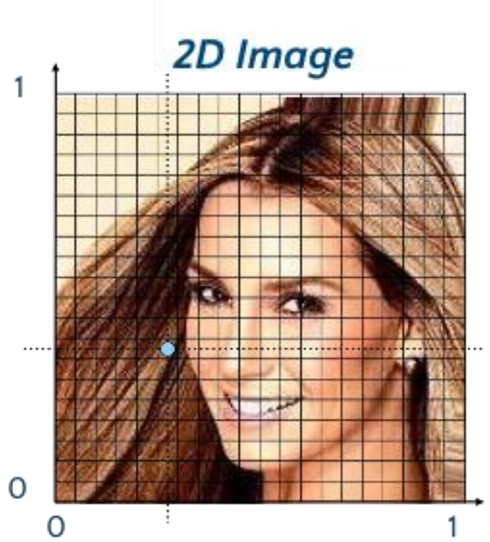
Temporal

Spatio-temporal

$f : \mathbb{R}^2 \to \mathbb{R}^3, f(x_1, x_2) = (r, g, b)$ $f : \mathbb{R}^3 \to \{0, 1\}, f(x_1, x_2, x_3) = p$ $f : \mathbb{R}^2 \to \mathbb{R}, f(\varphi, \lambda) = T$ $f : \mathbb{R}^3 \to \mathbb{R}^3, f(x_1, x_2, t) = (r, g, b)$

Introduction

- Focusing on images:

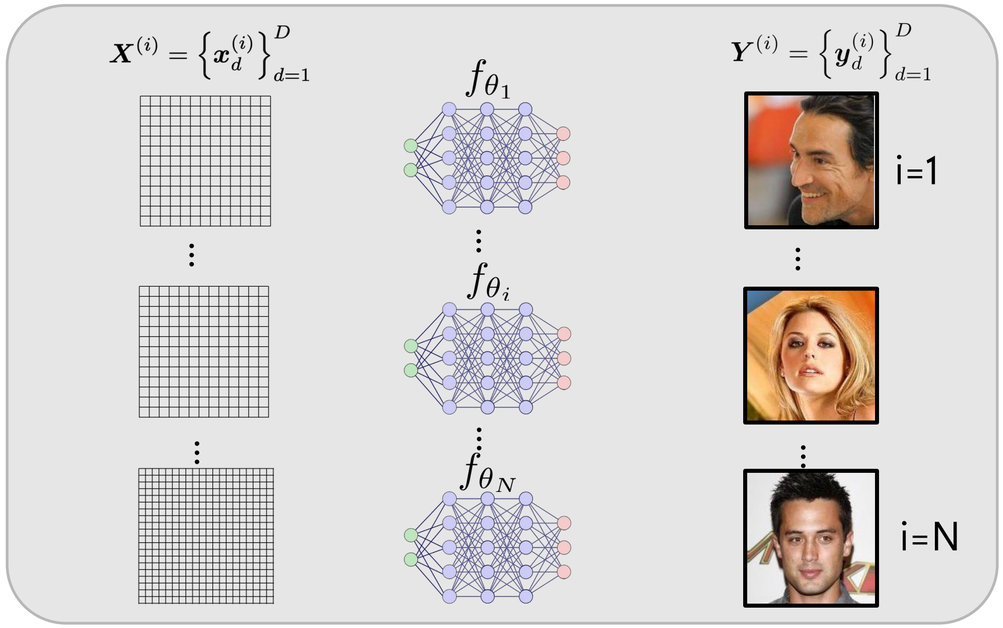


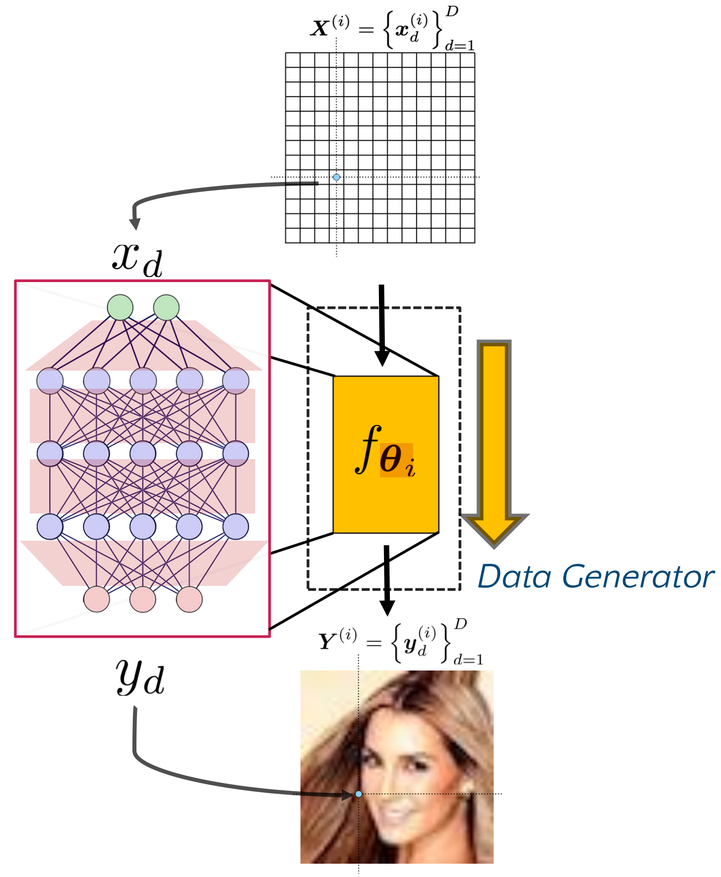
- Generator function $f : \boldsymbol{X} \rightarrow \boldsymbol{Y}$ creates this speficic image with the mapping $f(\boldsymbol{x}_d) = \boldsymbol{y}_d$, $d \in [1, ..., D]$
- Each pixel is now a pair $\{\boldsymbol{x}_d, \boldsymbol{y}_d\}$ where $x_d \in \mathbb{R}^2$, $y_d \in \mathbb{R}^3$
- Full image is a pair of sets $\boldsymbol{X} = \{\boldsymbol{x}_d\}_{d=1}^{D}, \quad \boldsymbol{Y}_d = \{\boldsymbol{y}_d\}_{d=1}^{D}$

Introduction

Implicit Neural Representations (INRs) [2-4]

Data generator $f_{\boldsymbol{\theta}_i}$ is unique to each image





[2] Sitzmann et at., 2020 [3] Mescheder et at., 2019 [4] Sitzmann et at., 2019

Introduction

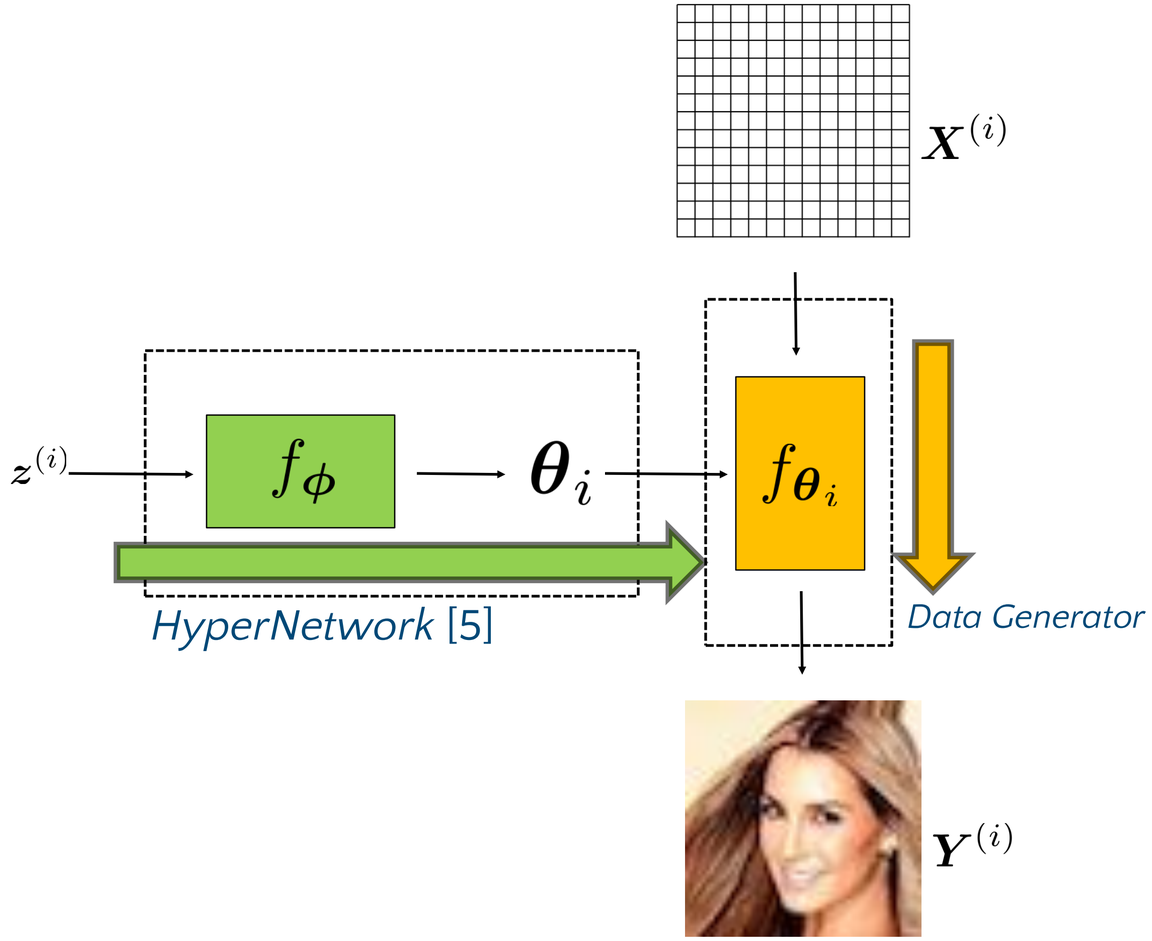
How to scale to large datasets?

How to map data to an INR?

Introduction

Hypernetworks [5]

Have $z^{(i)}$, a summary representation of image.



[5] Ha et at., 2017

Introduction

How to infer the latent representation ***z***?

$$p_\theta(\boldsymbol{z})$$

Related Work

GASP[6]

- Adversarial training:

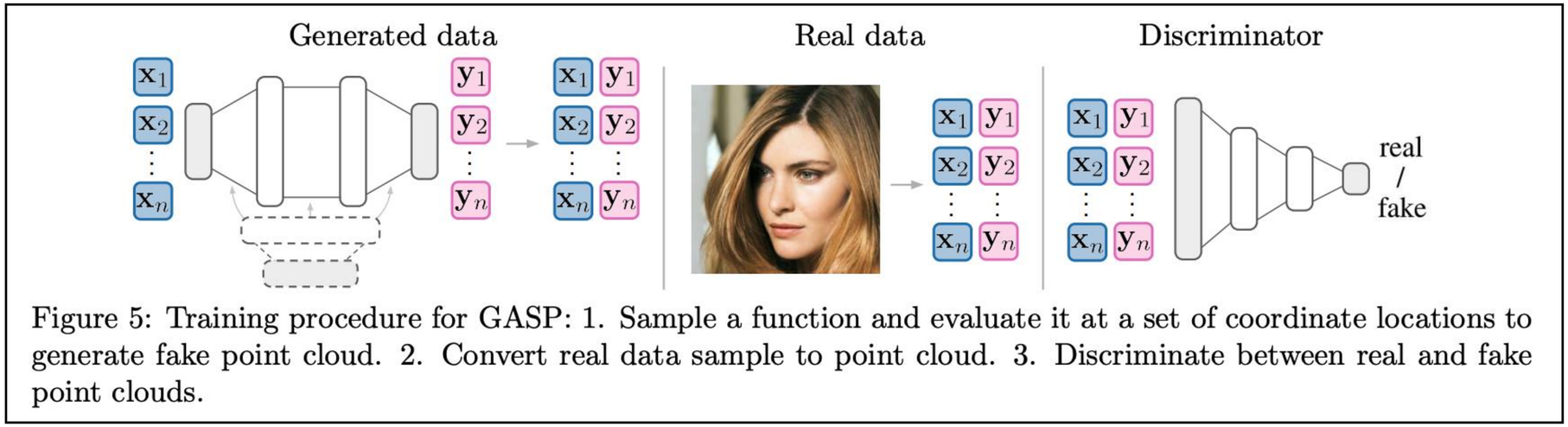


Figure 5: Training procedure for GASP: 1. Sample a function and evaluate it at a set of coordinate locations to generate fake point cloud. 2. Convert real data sample to point cloud. 3. Discriminate between real and fake point clouds.

✗ Can’t tackle inference related tasks.

[6] Dupont et at., 2020

Related Work

Functa[7]

- Decoupled training:
  1. Fit an INR per datapoint using SIREN[2] and **modulation vectors**, named **functas**.
  2. Train any generative model on the functa dataset of vectors.

✗ Computationally expensive inference.

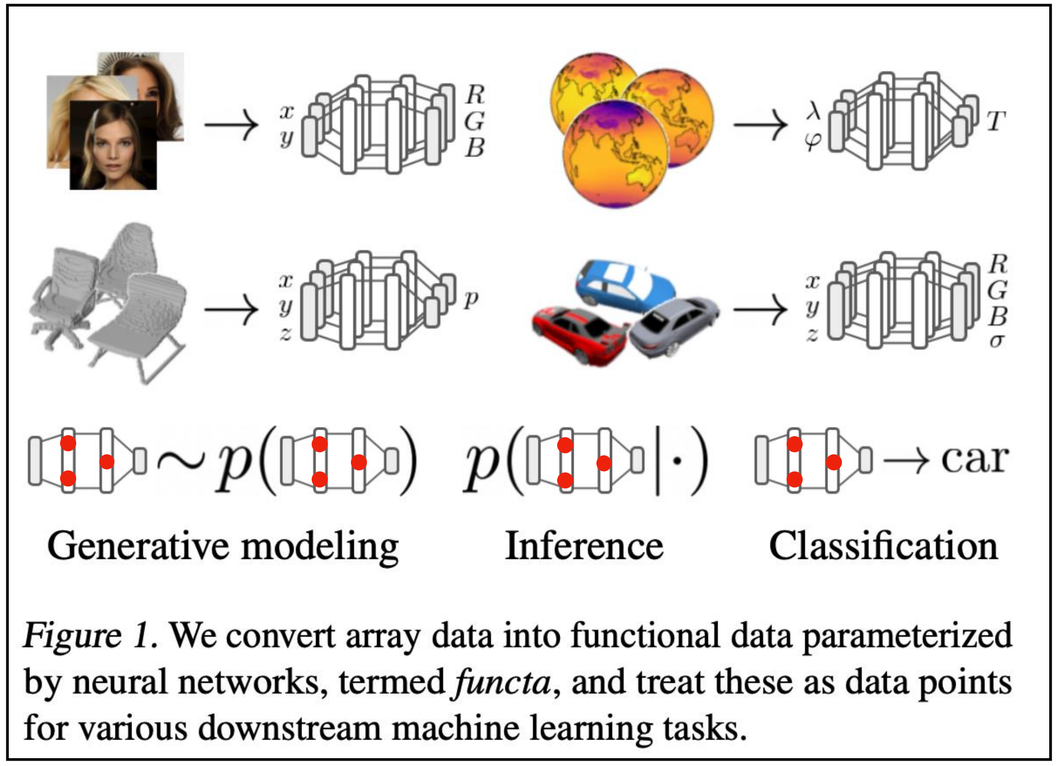


Figure 1. We convert array data into functional data parameterized by neural networks, termed *functa*, and treat these as data points for various downstream machine learning tasks.

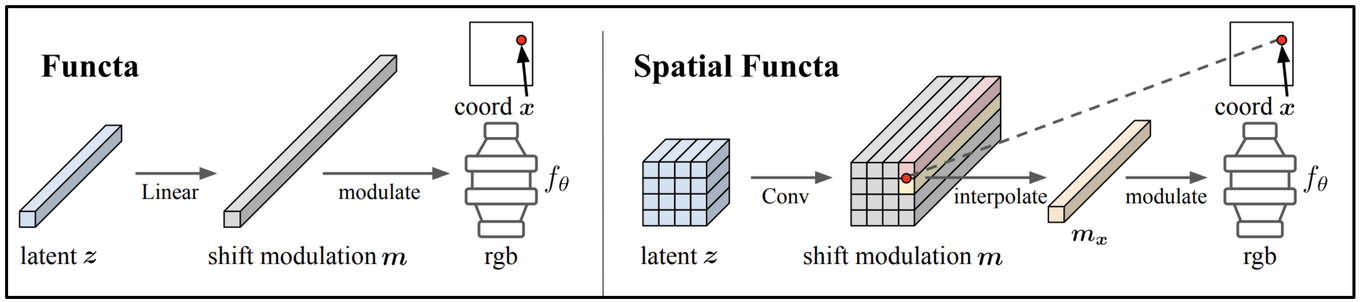
[7] Dupont et at., 2022 [2] Sitzmann et at., 2020

Related Work

Spatial Functa[8]

- Decoupled training:
  1. Fit an INR per datapoint using SIREN[8] and **modulation tensor**.
  2. Train any generative model on the functa dataset of tensors.

✗ Computationally expensive inference.



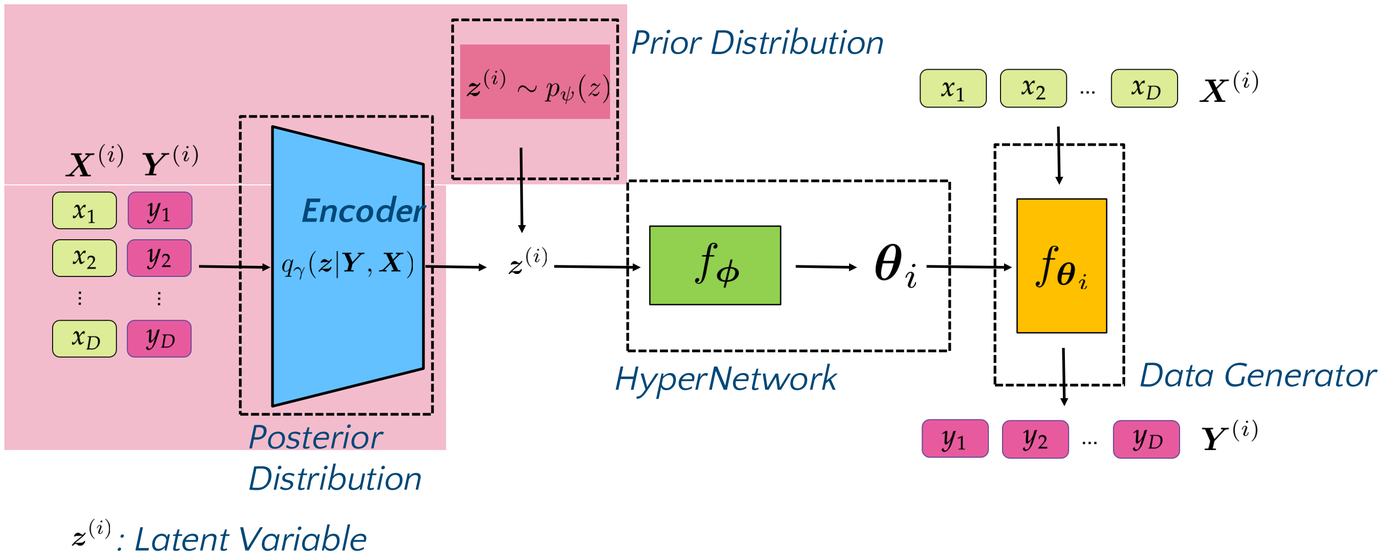
[8] Bauer et at., 2023

[2] Sitzmann et at., 2020

Related Work

VAMoH [9]

- Variational Inference
  - Requires flexible, learnable prior.



$$\mathcal{L}(\boldsymbol{Y}, \boldsymbol{X}; \psi, \phi, \boldsymbol{\gamma}) = \sum_{d=1}^{D} \mathbb{E}_{q_{\gamma_z}(\boldsymbol{z}|\boldsymbol{Y},\boldsymbol{X})} \left[\sum_{k=1}^{K} \log p_{\boldsymbol{\theta}_k} (\boldsymbol{y}_d \mid \boldsymbol{x}_d) \cdot \pi_{dk} \right] - D_{KL} \left(q_{\gamma_z}(\boldsymbol{z} \mid \boldsymbol{X}, \boldsymbol{Y}) \| p_{\psi_z}(\boldsymbol{z}) \right)$$

[9] Koyuncu et at., 2023

Related Work

VAMoH [9]

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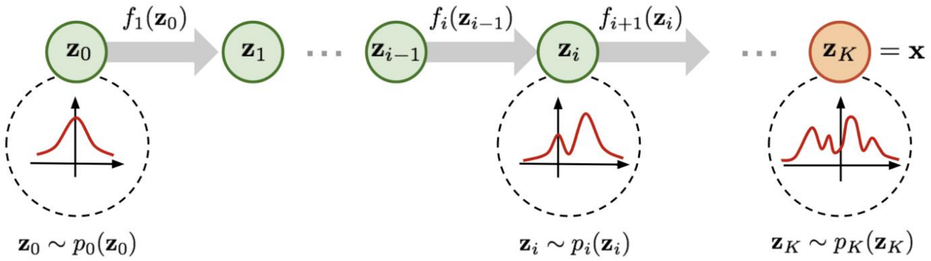
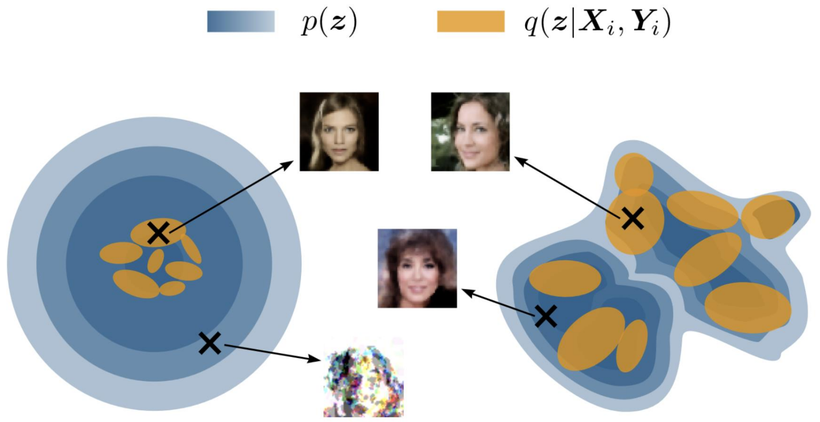




The ***hole*** problem

$$\mathcal{L}(\boldsymbol{Y}, \boldsymbol{X}; \psi, \phi, \boldsymbol{\gamma}) = \sum_{d=1}^{D} \mathbb{E}_{q_{\gamma_z}(\boldsymbol{z}|\boldsymbol{Y},\boldsymbol{X})} \left[\sum_{k=1}^{K} \log p_{\boldsymbol{\theta}_k} (\boldsymbol{y}_d \mid \boldsymbol{x}_d) \cdot \pi_{dk} \right] - D_{KL} \left(q_{\gamma_z}(\boldsymbol{z} \mid \boldsymbol{X}, \boldsymbol{Y}) \| p_{\psi_z}(\boldsymbol{z}) \right)$$

[9] Koyuncu et at., 2023

Motivation

Flexibility of the latent space in [6, 7, 9]

✕ Poor generation quality.

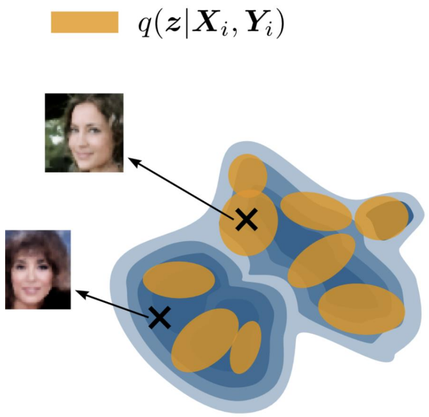
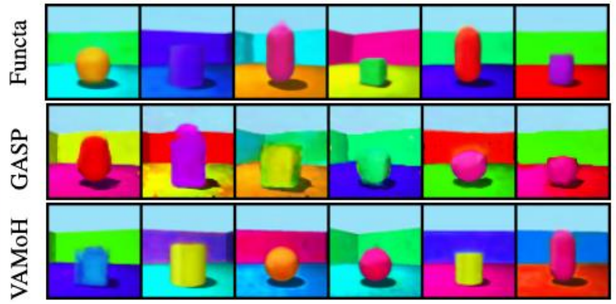


Image Reconstruction with VAMoH

(a) CelebA HQ

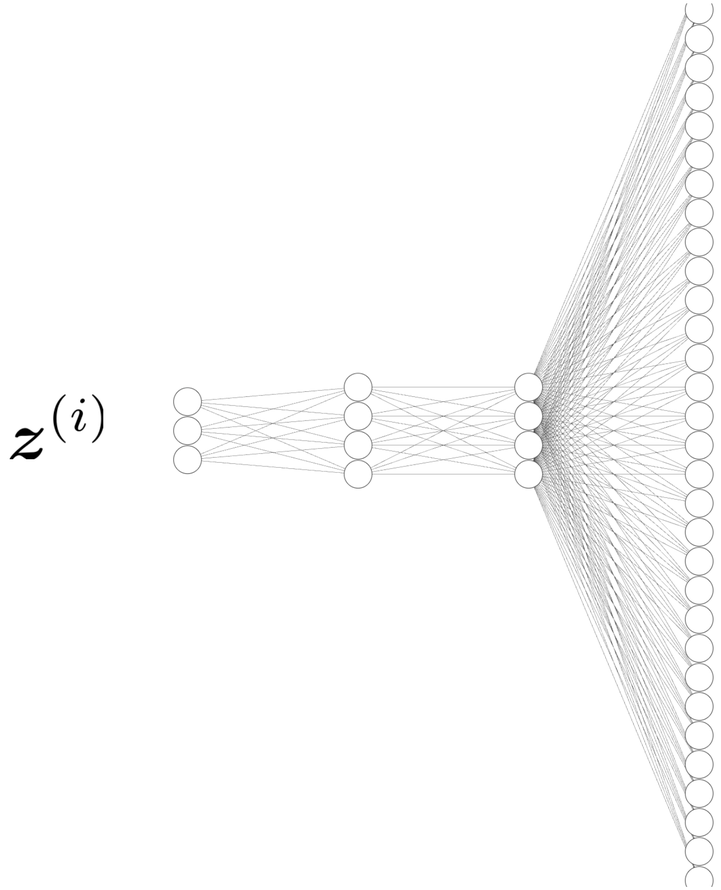


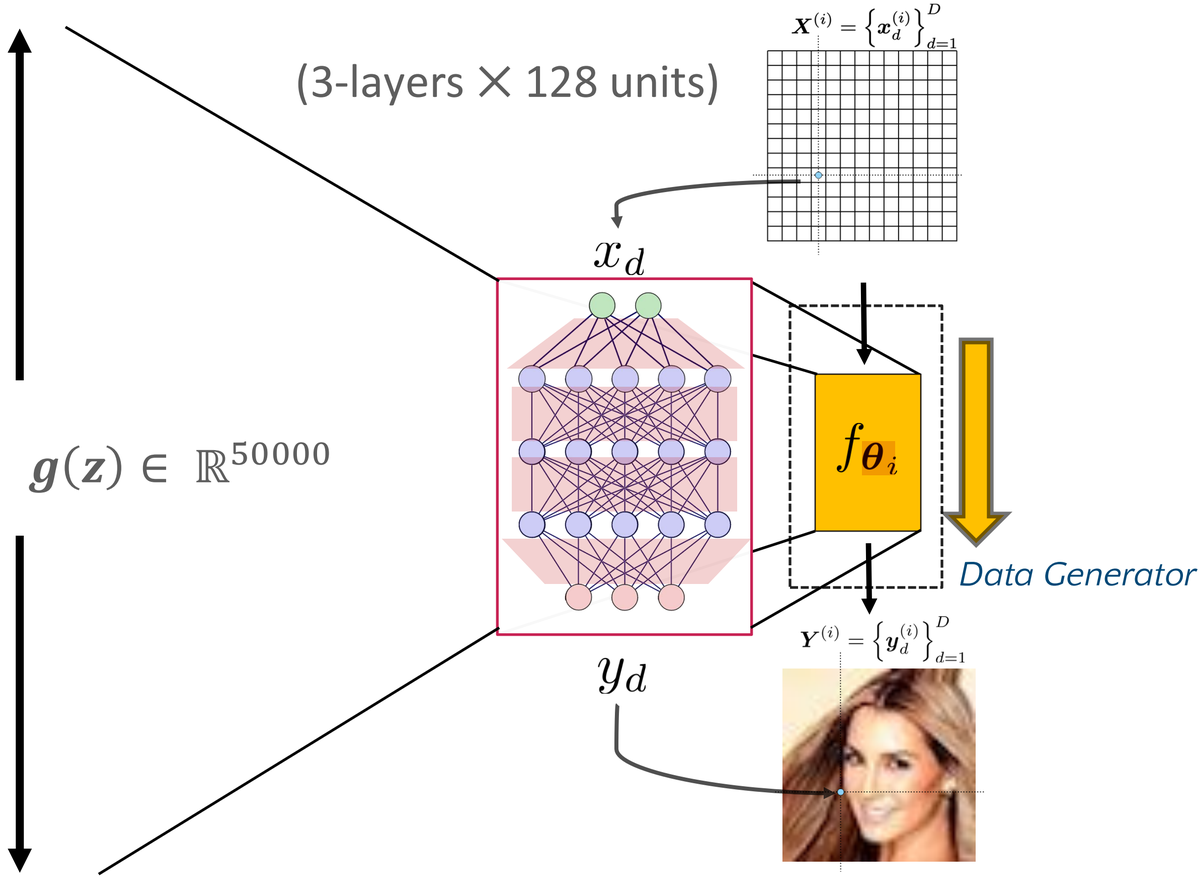
(b) Shapes3D

[6] Dupont et at., 2020 [7] Dupont et at., 2022 [9] Koyuncu et at., 2023

Motivation

Hypernetwork bottleneck in [6, 9]





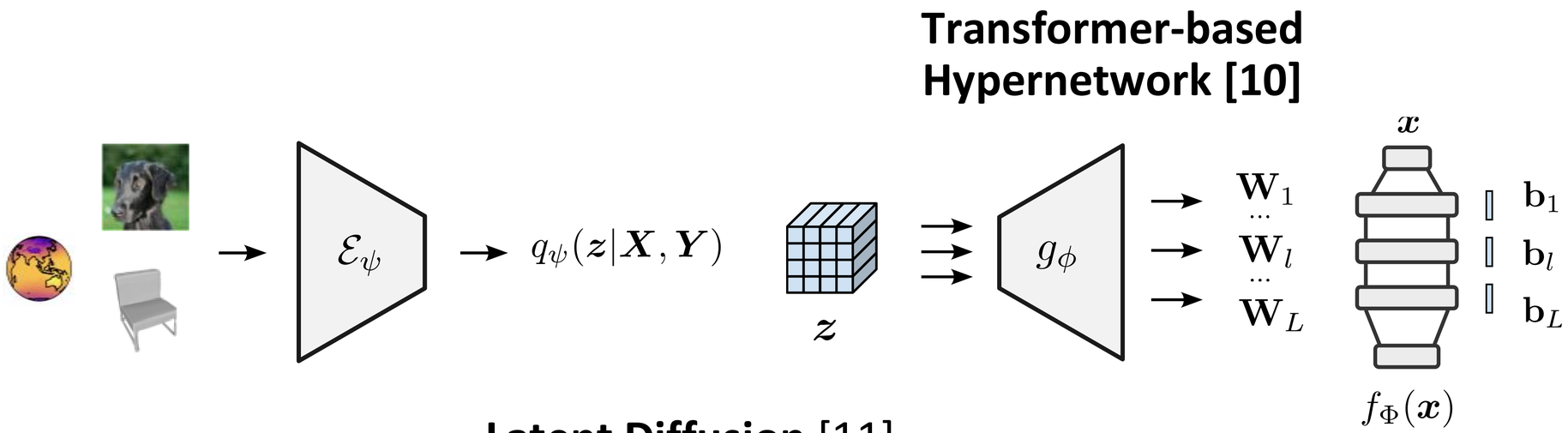
[6] Dupont et at., 2020

[9] Koyuncu et at., 2023

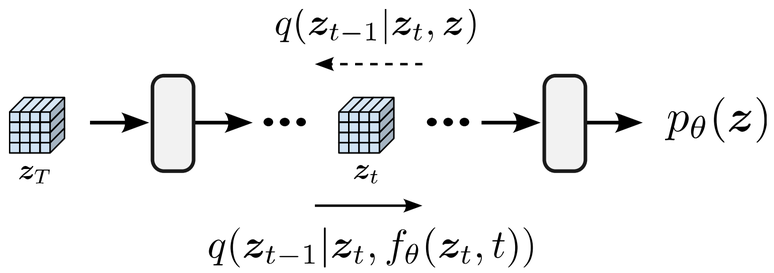
Proposed method

Latent Diffusion Models of INRs

LDMI [1]



Latent Diffusion [11]



[1] Peis et at., 2025 [10] Chen et at., 2024 [11] Rombach et at., 2021

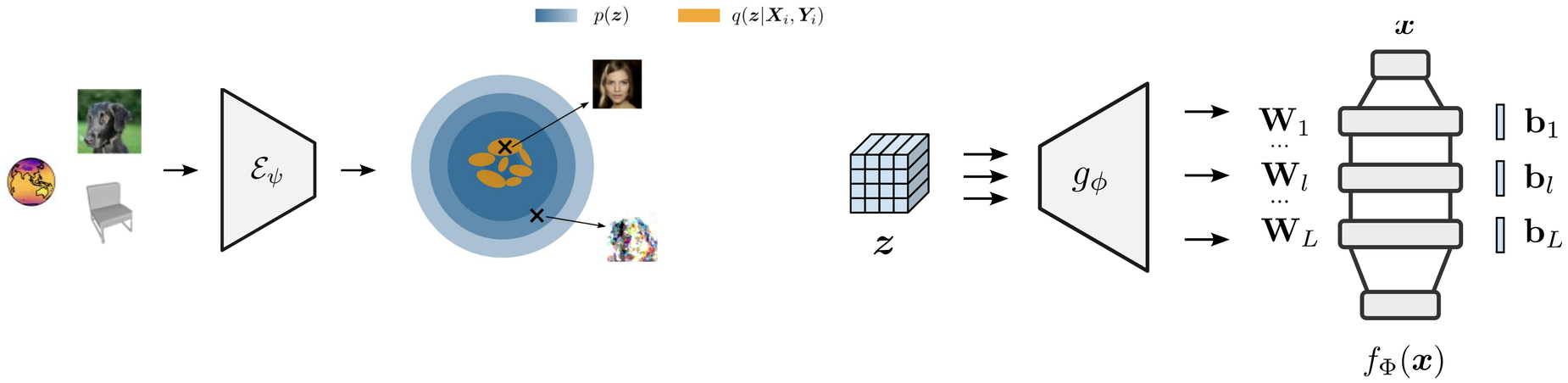
Latent Diffusion Models of INRs

The HD decoder

We will **firstly** train an *"under-regularized"* autoencoder to accurately represent data in a (tensor-shaped) latent space.

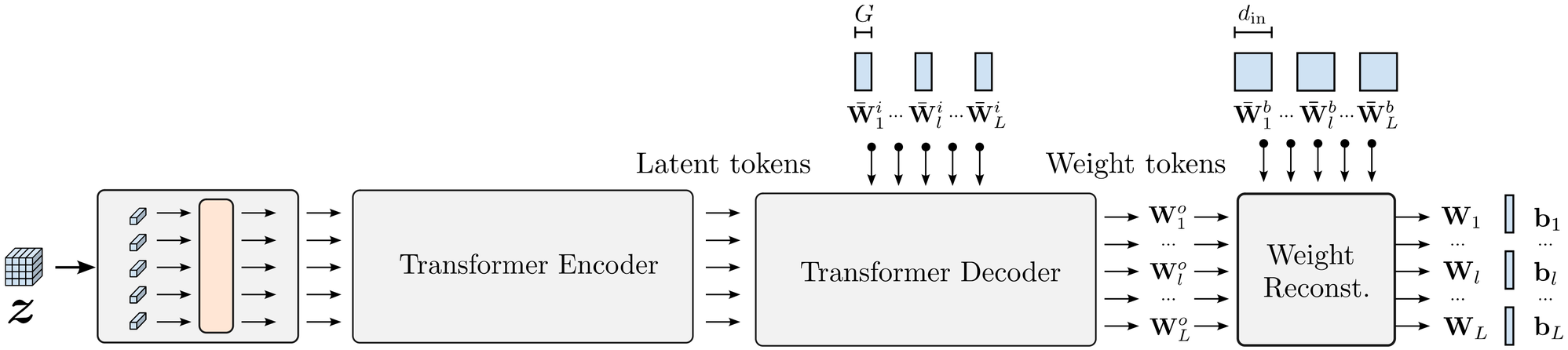
- The latents are mapped into INRs using our **transformer–based hypernetwork decoder**.

$$\mathcal{L}_{\text{VAE}}(\phi, \psi) = \mathbb{E}_{q_\psi(\boldsymbol{z}|\boldsymbol{X})}\left[\log p_\Phi(\boldsymbol{X})\right] - \beta \cdot D_{\text{KL}}\left(q_\psi(\boldsymbol{z} \mid \boldsymbol{X}) \| p(\boldsymbol{z})\right) + \mathcal{L}_{\text{perceptual}} + \mathcal{L}_{\text{GAN}}$$



Latent Diffusion Models of INRs

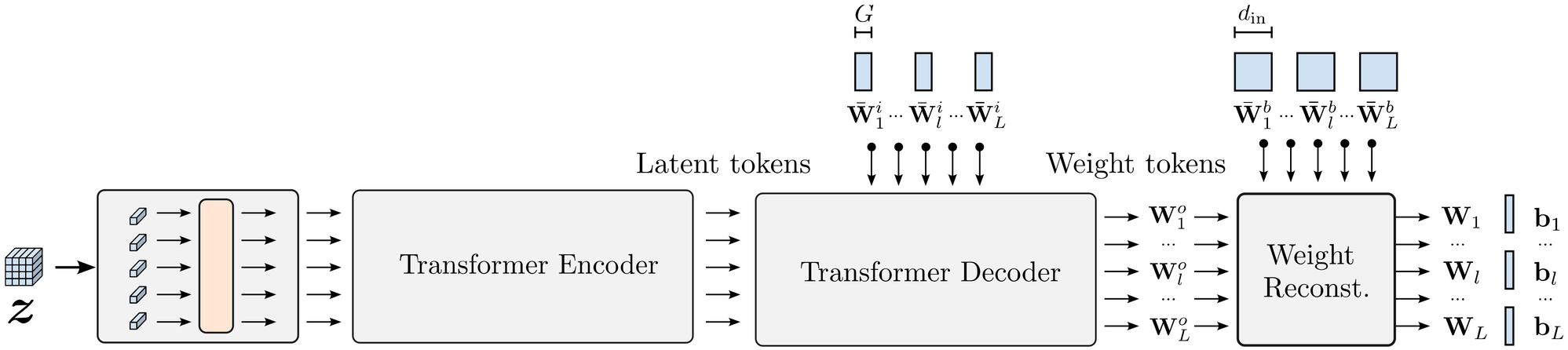
The HD decoder



- The **latent tokens** come from tokenizing ***z*** (following ViT [32]) and processing them via a Transformer Encoder.
- The **weight tokens** are columns of the weight matrices.

Latent Diffusion Models of INRs

The HD decoder



- A set of G initial weight tokens $\bar{\boldsymbol{w}}^i$ per layer (learnable, globally shared) cross-attend the *latent tokens*, $\bar{\boldsymbol{w}}^i$, to produce specific weights $\boldsymbol{w}^o$.

- The final weight tokens, $\boldsymbol{w}$, are obtained by expanding $\boldsymbol{w}^o$ using a learnable, globally shared template $\bar{\boldsymbol{w}}^b$:

$$\boldsymbol{w}_c = \mathcal{R}\left(\boldsymbol{w}^{\mathrm{o}}_{\lfloor c/k \rfloor}, \bar{\boldsymbol{w}}^{\mathrm{b}}_c\right) = \left(1 + \boldsymbol{w}^{\mathrm{o}}_{\lfloor c/k \rfloor}\right) \odot \bar{\boldsymbol{w}}^{\mathrm{b}}_c$$

Latent Diffusion Models of INRs

DDPM [13]

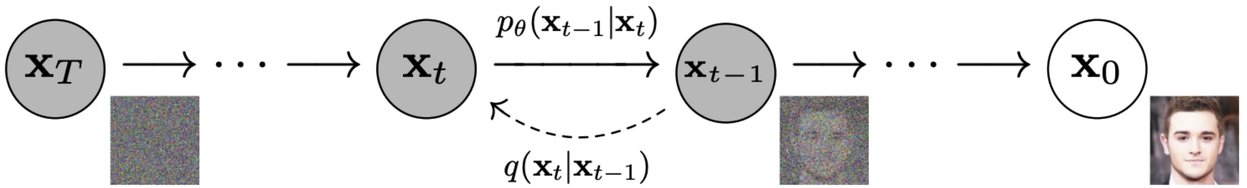


Figure 2: The directed graphical model considered in this work.

$$p_\theta\left(\mathbf{x}_{0:T}\right) := p\left(\mathbf{x}_T\right) \prod_{t=1}^{T} p_\theta\left(\mathbf{x}_{t-1} \mid \mathbf{x}_t\right), \quad p_\theta\left(\mathbf{x}_{t-1} \mid \mathbf{x}_t\right) := \mathcal{N}\left(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta\left(\mathbf{x}_t, t\right), \boldsymbol{\Sigma}_\theta\left(\mathbf{x}_t, t\right)\right)$$

$$q\left(\mathbf{x}_{1:T} \mid \mathbf{x}_0\right) := \prod_{t=1}^{T} q\left(\mathbf{x}_t \mid \mathbf{x}_{t-1}\right), \quad q\left(\mathbf{x}_t \mid \mathbf{x}_{t-1}\right) := \mathcal{N}\left(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I}\right)$$

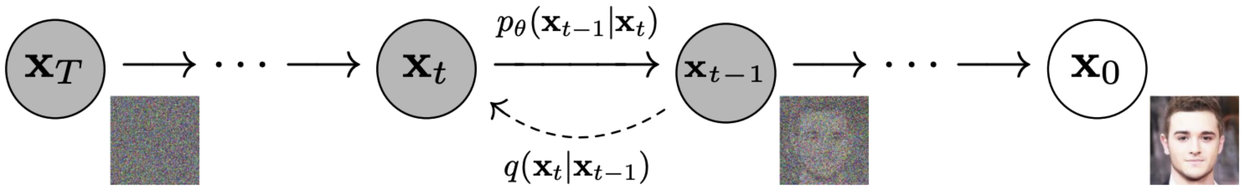
$$q\left(\mathbf{x}_t \mid \mathbf{x}_0\right) = \mathcal{N}\left(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, \left(1-\bar{\alpha}_t\right)\mathbf{I}\right) \qquad \alpha_t := 1-\beta_t \qquad \bar{\alpha}_t := \prod_{s=1}^{t} \alpha_s$$

$$\mathbb{E}_q[\underbrace{D_{\mathrm{KL}}\left(q\left(\mathbf{x}_T \mid \mathbf{x}_0\right) \| p\left(\mathbf{x}_T\right)\right)}_{L_T} + \sum_{t>1} \underbrace{D_{\mathrm{KL}}\left(q\left(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0\right) \| p_\theta\left(\mathbf{x}_{t-1} \mid \mathbf{x}_t\right)\right)}_{L_{t-1}} \underbrace{-\log p_\theta\left(\mathbf{x}_0 \mid \mathbf{x}_1\right)}_{L_0}]$$

[13] Ho et at., 2020

Latent Diffusion Models of INRs

DDPM [13]



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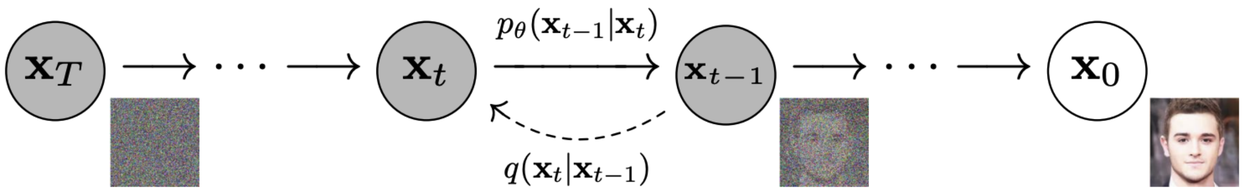
$$\mathbb{E}_{\mathbf{x}_0, \boldsymbol{\epsilon}}\left[\frac{\beta_t^2}{2\sigma_t^2 \alpha_t\left(1-\bar{\alpha}_t\right)}\left\|\boldsymbol{\epsilon}-\boldsymbol{\epsilon}_\theta\left(\sqrt{\bar{\alpha}_t}\mathbf{x}_0+\sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t\right)\right\|^2\right]$$

[13] Ho et at., 2020

Latent Diffusion Models of INRs

DDPM [13]



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$$\mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon}}\left[\frac{\beta_t^2}{2\sigma_t^2\alpha_t\left(1-\bar{\alpha}_t\right)}\left\|\boldsymbol{\epsilon}-\boldsymbol{\epsilon}_\theta\left(\sqrt{\bar{\alpha}_t}\mathbf{x}_0+\sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon},t\right)\right\|^2\right]$$

$$\Downarrow$$

$$L_{\text{simple}}\left(\theta\right):=\mathbb{E}_{t,\mathbf{x}_0,\boldsymbol{\epsilon}}\left[\left\|\boldsymbol{\epsilon}-\boldsymbol{\epsilon}_\theta\left(\sqrt{\bar{\alpha}_t}\mathbf{x}_0+\sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon},t\right)\right\|^2\right]$$

[13] Ho et at., 2020

Latent Diffusion Models of INRs

DDIM [14]

- Define a Non-Markovian Inference Model:

$$p_\theta\left(\boldsymbol{z}_{t-1} \mid \boldsymbol{z}_t\right)=\begin{cases}\mathcal{N}\left(\hat{\boldsymbol{z}}, \sigma_1^2 \boldsymbol{I}\right) & \text{if } t=1 \\ q\left(\boldsymbol{z}_{t-1} \mid \boldsymbol{z}_t, \hat{\boldsymbol{z}}\right) & \text{otherwise}\end{cases}$$

- The objective is the same!

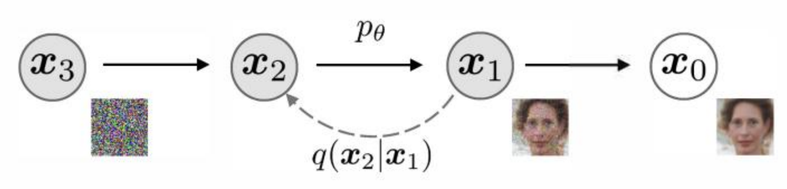
$$L_{\text{simple}}(\theta):=\mathbb{E}_{t, \mathbf{x}_0, \boldsymbol{\epsilon}}\left[\left\|\boldsymbol{\epsilon}-\boldsymbol{\epsilon}_\theta\left(\sqrt{\bar{\alpha}_t} \mathbf{x}_0+\sqrt{1-\bar{\alpha}_t} \boldsymbol{\epsilon}, t\right)\right\|^2\right]$$

- Using the same model, you can sample in fewer steps!

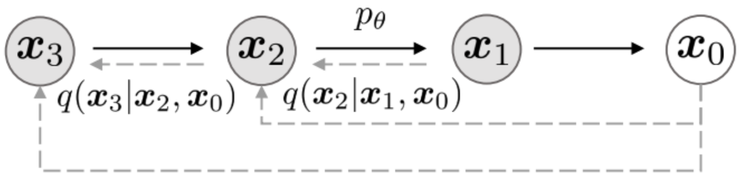
$$p_\theta^{(\tau_i)}\left(\boldsymbol{x}_{\tau_{i-1}} \mid \boldsymbol{x}_{\tau_i}\right)=q_{\sigma, \tau}\left(\boldsymbol{x}_{\tau_{i-1}} \mid \boldsymbol{x}_{\tau_i}, f_\theta^{(\tau_i)}\left(\boldsymbol{x}_{\tau_{i-1}}\right)\right) \quad \text{if } i \in[S], i>1$$

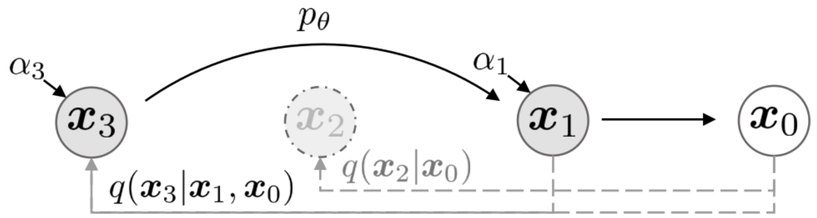
$$p_\theta^{(t)}\left(\boldsymbol{x}_0 \mid \boldsymbol{x}_t\right)=\mathcal{N}\left(f_\theta^{(t)}\left(\boldsymbol{x}_t\right), \sigma_t^2 \boldsymbol{I}\right) \quad \text{otherwise},$$

Markovian (DDPM)



Non-Markovian (DDIM)





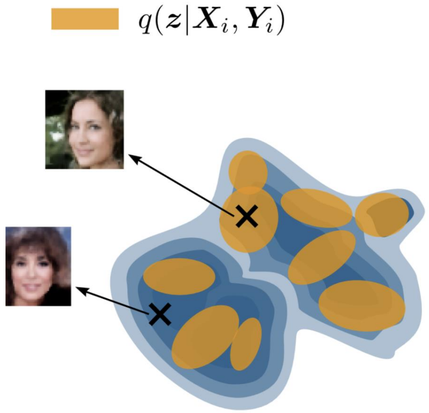
[14] Song et at., 2021

Latent Diffusion Models of INRs

Latent Diffusion Models [11]

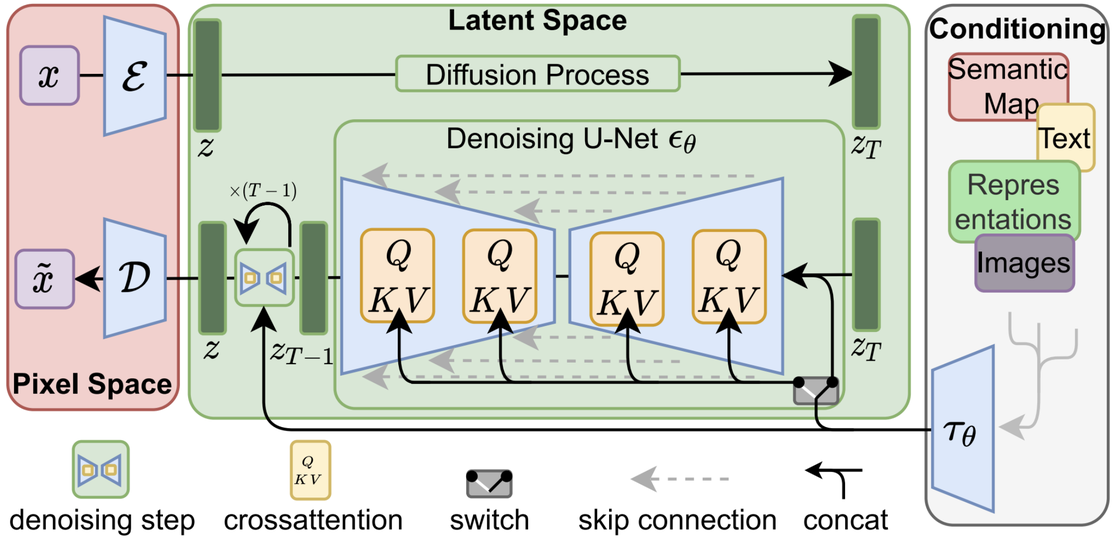
- First stage:

$$\mathcal{L}_{\text{VAE}}(\phi, \psi) = \mathbb{E}_{q_\psi(\boldsymbol{z}|\boldsymbol{X})}\left[\log p_\Phi(\boldsymbol{X})\right] - \beta \cdot D_{\text{KL}}\left(q_\psi(\boldsymbol{z} \mid \boldsymbol{X}) \| p(\boldsymbol{z})\right), + \mathcal{L}_{\text{perceptual}} + \mathcal{L}_{\text{GAN}}$$



- Second stage:

$$\mathcal{L}_{\text{DDPM}} = \mathbb{E}_{\boldsymbol{X},\boldsymbol{z},\epsilon,t}\left[\lambda(t) \left\|\epsilon - \epsilon_\theta\left(\boldsymbol{z}_t, t\right)\right\|^2\right],$$



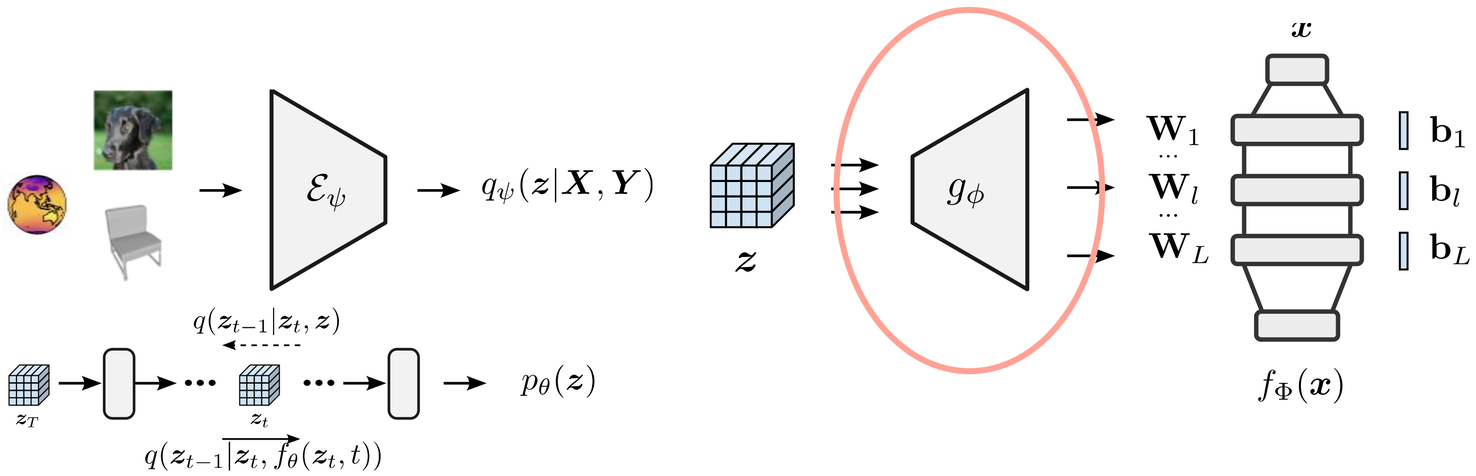
[11] Rombach et at., 2021

Latent Diffusion Models of INRs

Hyper-Transforming

- We can download pre-trained LDMs and just re-train only our decoder!

$$\mathcal{L}_{\text{HT}}(\phi) = \mathbb{E}_{q_\psi(\boldsymbol{z}|\boldsymbol{X},\boldsymbol{Y})}\left[\log p_\Phi(\boldsymbol{Y} \mid \boldsymbol{X})\right] + \mathcal{L}_{\text{perceptual}} + \mathcal{L}_{\text{GAN}}$$



Pretrained LDMs

Datset	Task	Model	FID	IS	Prec	Recall	
CelebA-HQ	Unconditional Image Synthesis	LDM-VQ-4 (200 DDIM steps, eta=0)	5.11 (5.11)	3.29	0.72	0.49	https://omr diffusion/c
FFHQ	Unconditional Image Synthesis	LDM-VQ-4 (200 DDIM steps, eta=1)	4.98 (4.98)	4.50 (4.50)	0.73	0.50	https://omr diffusion/ff
LSUN-Churches	Unconditional Image Synthesis	LDM-KL-8 (400 DDIM steps, eta=0)	4.02 (4.02)	2.72	0.64	0.52	https://omr diffusion/ls

Experiments

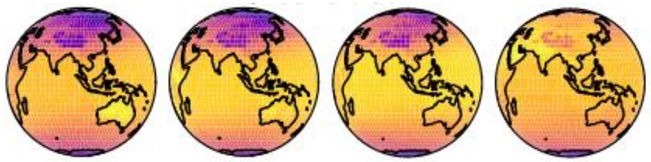
Datasets

CelebA-HQ (64x64)

CelebA-HQ (256x256)

ImageNet (256x256)

ERA5 (Polar)



ShapeNET (Voxels)

Experiments

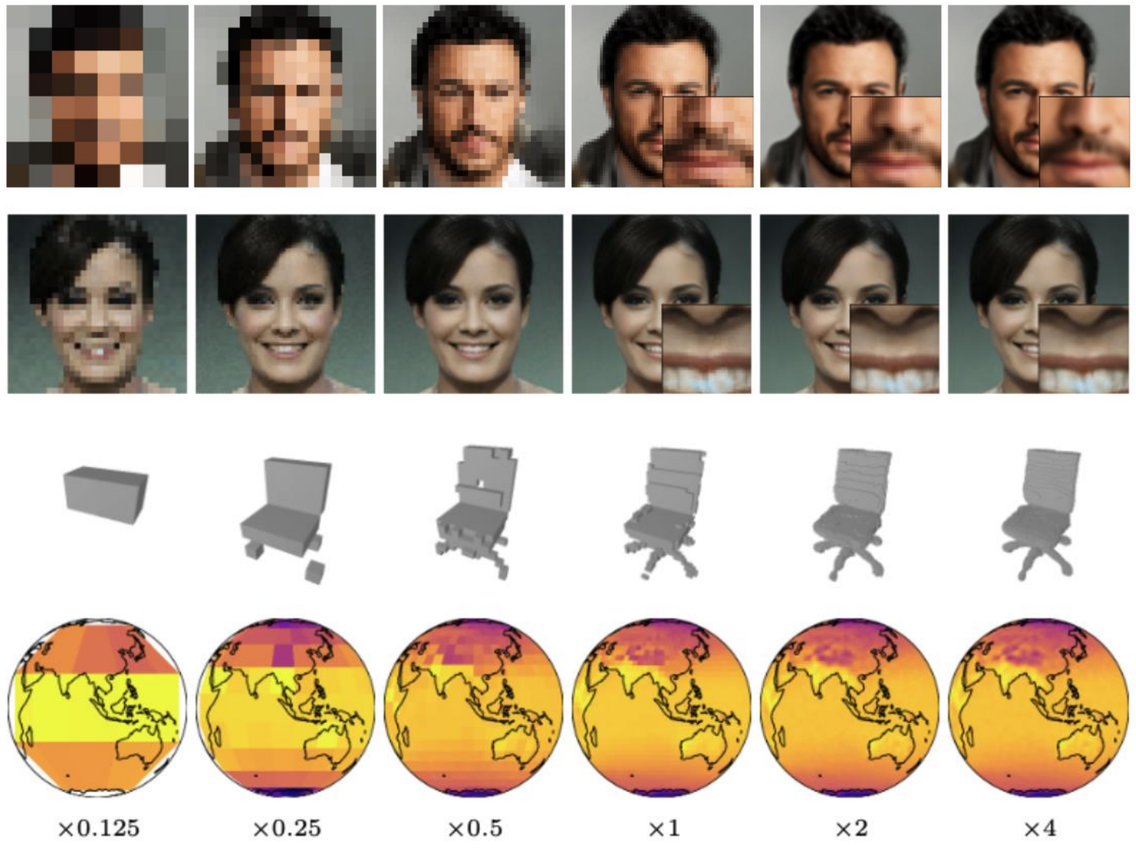
Baselines

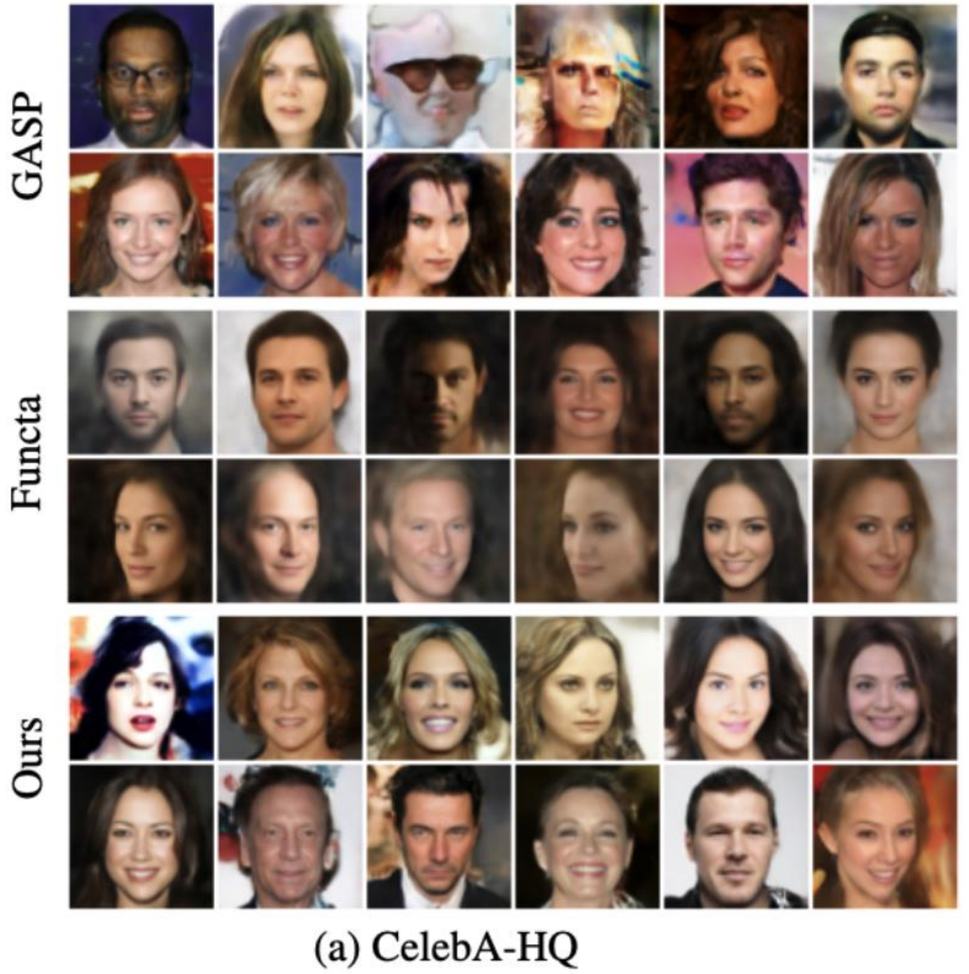
Model	Approach	Training Procedure	Generation	Reconstruction, Imputation, Super Resolution	Scalable	Flexible
GASP (2021) [5]	GAN	Minimax	Forward Pass	❌	❌	❌
Functa (2022) [6]	Flow-based	Bilevel optimization	+ Extra Generative Model	Optimization procedure(s) per sample	❌	❌
VaMoH (ours)	VAE-based	**Single optimization**	**Forward Pass**	**Forward pass**	❌	❌
LDMI (ours)	LDM-based	**Hyper-Transforming**	**Forward Pass**	**Forward pass**	✅	✅

LDMI enhances efficiency, scalability and quality of the learned representations.

Experiments

Generation





(a) CelebA-HQ

Experiments

Reconstruction

Model	PSNR (dB) ↑	FID ↓	HN Params ↓
CelebA-HQ (64 × 64)			
GASP [Dupont et al., 2022a]	-	**7.42**	25.7M
Functa [Dupont et al., 2022b]	≤ **30.7**	40.40	-
VAMoH [Koyuncu et al., 2023]	23.17	66.27	25.7M
LDMI	24.80	18.06	**8.06M**
ImageNet (256 × 256)			
Spatial Functa [Bauer et al., 2023]	≤ 38.4	≤ 8.5	-
LDMI	20.69	**6.94**	102.78M

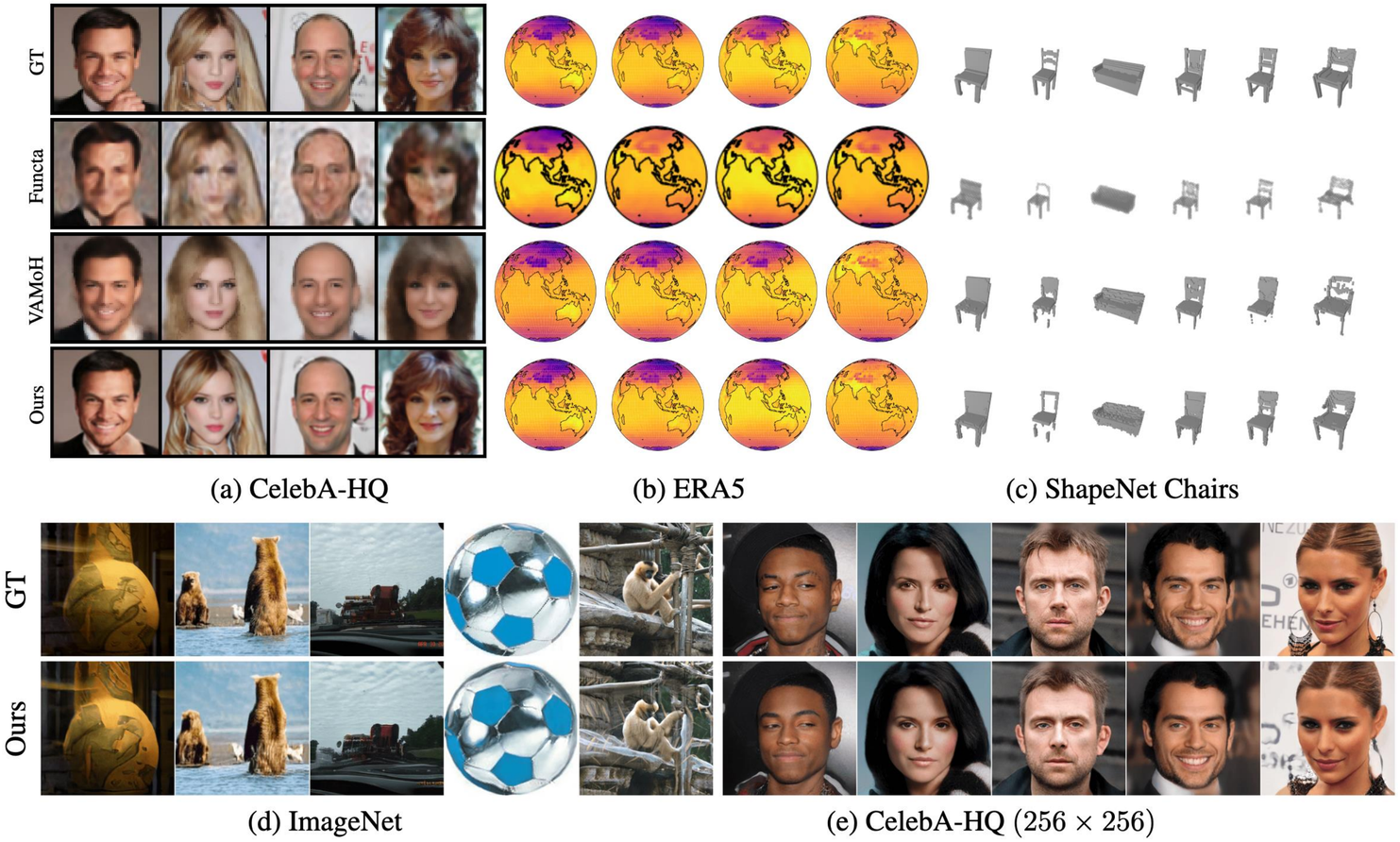
Table 1: Metrics on CelebA-HQ and ImageNet.

Model	Chairs (PSNR) ↑	ERA5 (PSNR) ↑
Functa [Dupont et al., 2022b]	29.2	34.9
VAMoH [Koyuncu et al., 2023]	38.4	39.0
LDMI	**38.8**	**44.6**

Table 2: Reconstruction quality (PSNR in dB) on ShapeNet Chairs and ERA5 climate data, demonstrating LDMI's strong generalization capabilities across modalities. Note that GASP is omitted as it is not applicable to INR reconstruction tasks.

Method	HN Params	INR Weights	Ratio (INR/HN)
GASP/VAMoH	25.7M	50K	0.0019
LDMI	**8.06M**	**330K**	**0.0409**

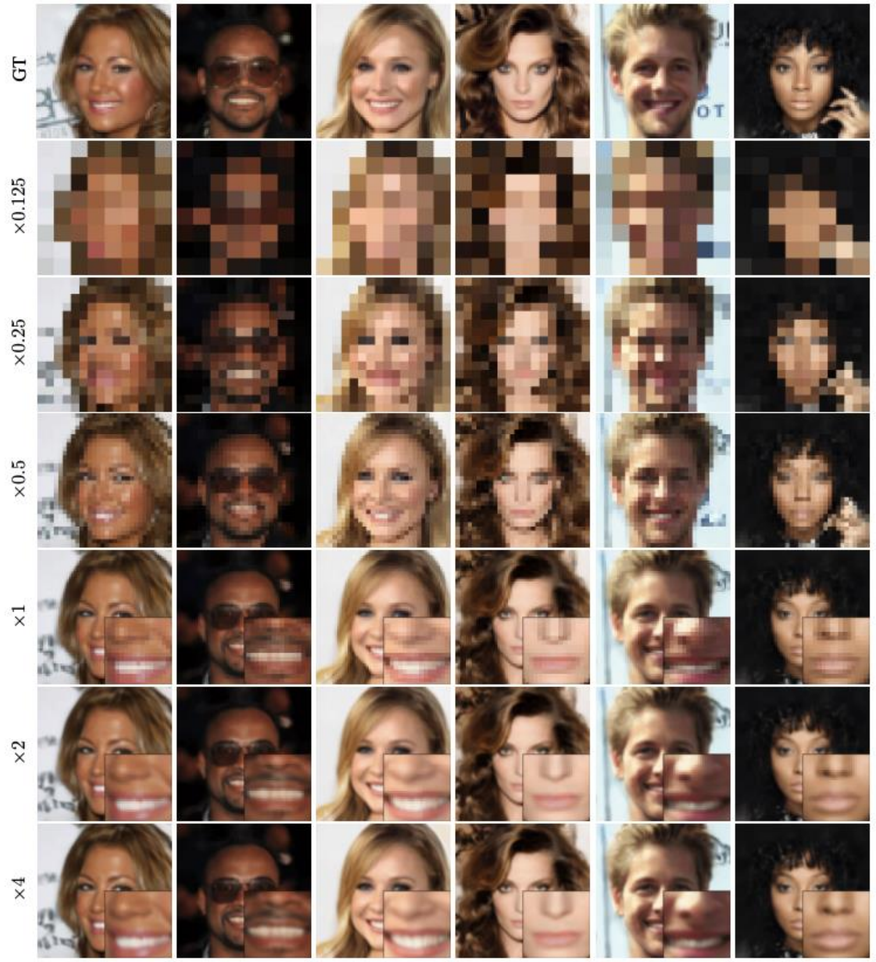
Table 3: Parameter efficiency of LDMI.



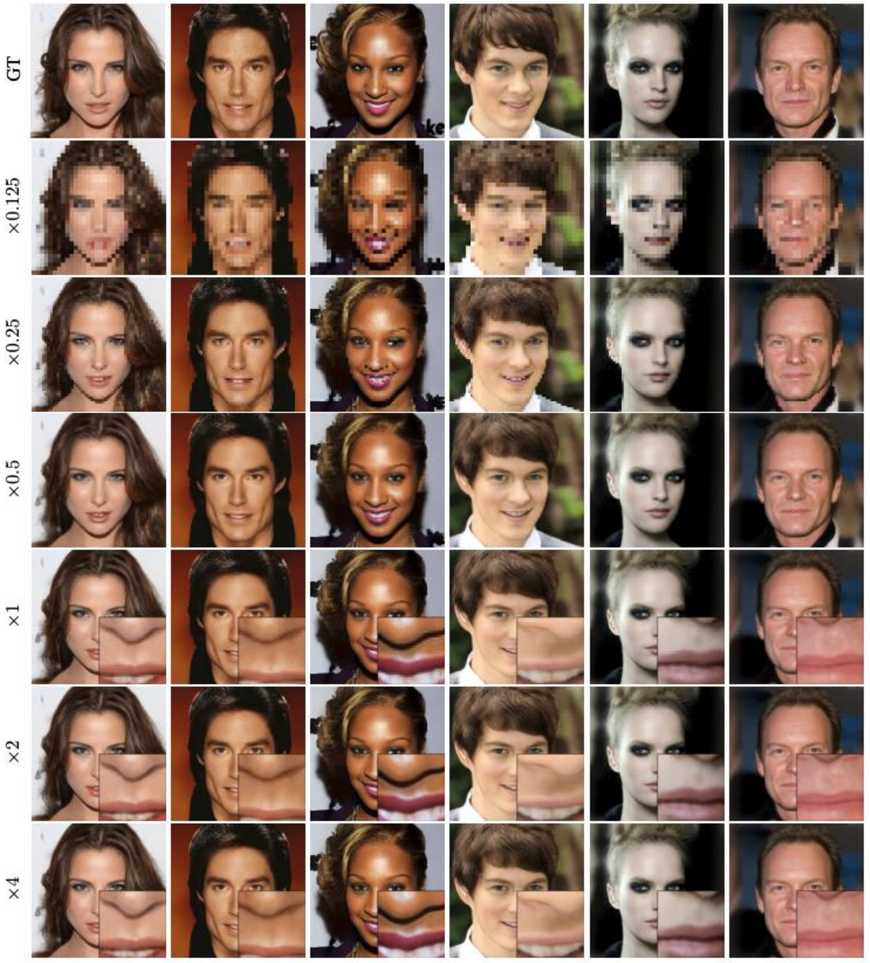
Experiments

Reconstruction

CelebA-HQ (64x64)



CelebA-HQ (256x256)



Experiments

Data completion

VAMoH

LDMI

Conclusion

Thanks to using **Latent Diffusion** and a novel **Transformer-based hypernetwork**, **LDMI** enhances

- Resolution-agnostic generation.
- Resolution-agnostic reconstruction.

While:

✓ Being scalable.

✓ Being efficient in parameter usage.

✓ Working with multiple data modalities.

✓ Allowing for generation of **bigger INRs** and more complex data.

Thank you!

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