Implicit Scene Representations and Neural Rendering

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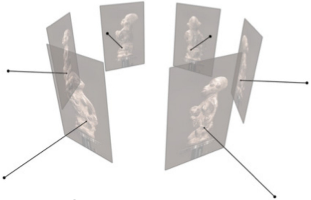
Implicit Scene Representations for 3D Reconstruction

Traditional 3D Reconstruction Pipeline

Input Images

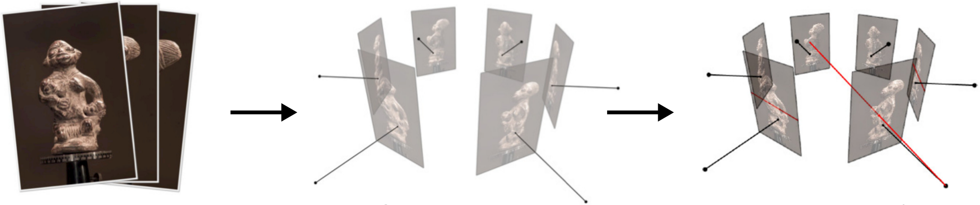
Traditional 3D Reconstruction Pipeline

Input Images



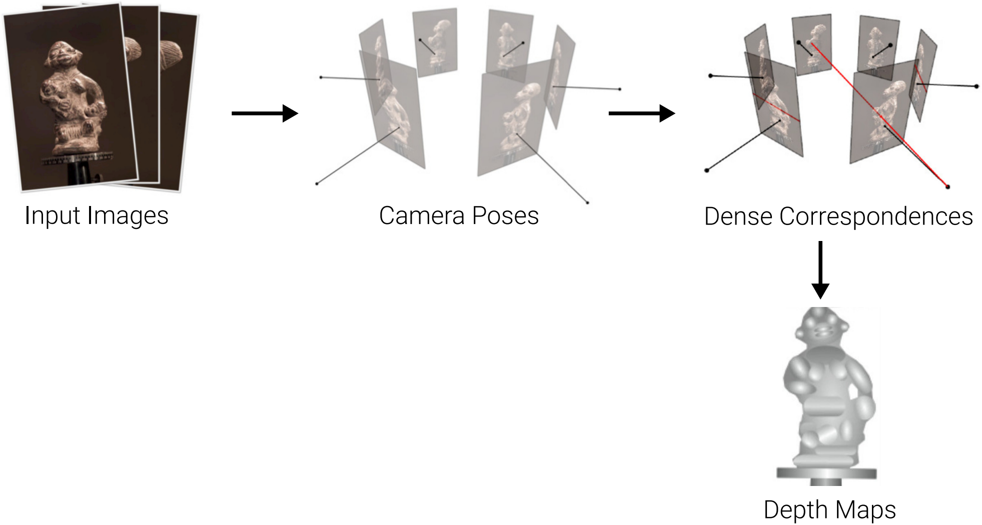
Camera Poses

Traditional 3D Reconstruction Pipeline



Input Images → Camera Poses → Dense Correspondences

Traditional 3D Reconstruction Pipeline



Traditional 3D Reconstruction Pipeline

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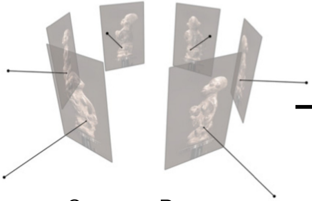
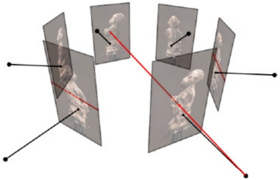
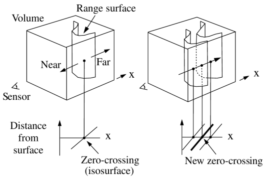


Camera Poses



Dense Correspondences

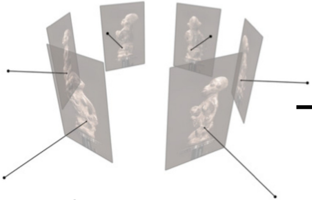
Depth Maps



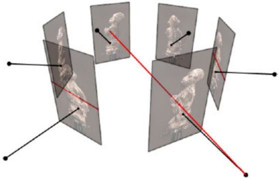
Depth Map Fusion

Traditional 3D Reconstruction Pipeline

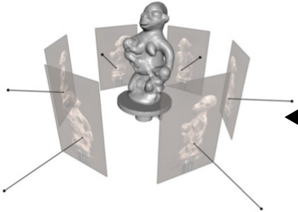
Input Images



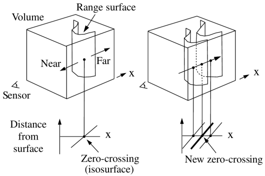
Camera Poses



Dense Correspondences



3D Reconstruction

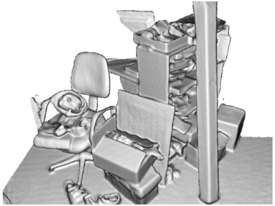


Depth Map Fusion

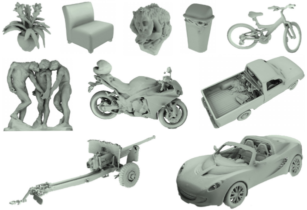
Depth Maps

Can we **learn** 3D reconstruction **from data**?

3D Datasets and Repositories



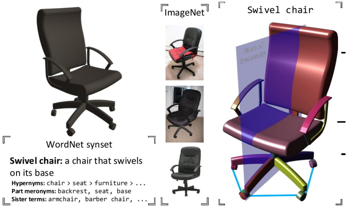
[Newcombe et al., 2011]



[Choi et al., 2011]

[Dai et al., 2017]

[Wu et al., 2015]

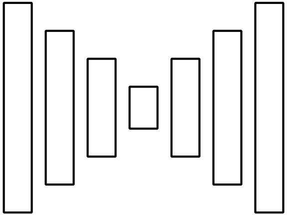


[Chang et al., 2015]

[Chang et al., 2017]

3D Reconstruction from a 2D Image

Input Images



Neural Network

3D Reconstruction

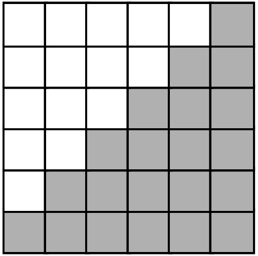
What is a good output representation?

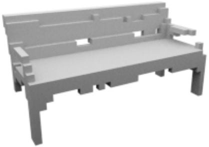
Learning-based 3D Reconstruction

Voxels:

- **Discretization** of 3D space into grid
- Easy to process with neural networks
- Cubic memory $O(n^3) \Rightarrow$ limited resolution
- Manhattan world bias

[Maturana et al., IROS 2015]

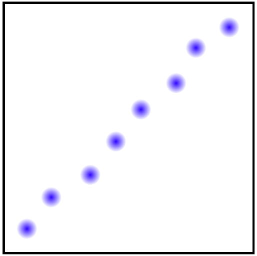




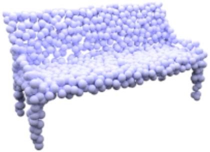
Learning-based 3D Reconstruction

Points:

- **Discretization** of surface into 3D points
- Does not model connectivity / topology
- Limited number of points
- Global shape description



[Fan et al., CVPR 2017]

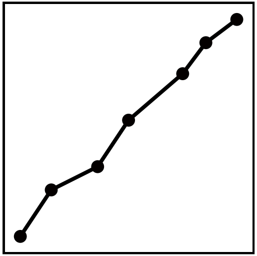


Learning-based 3D Reconstruction

Meshes:

- **Discretization** into vertices and faces
- Limited number of vertices / granularity
- Requires class-specific template – or –
- Leads to self-intersections

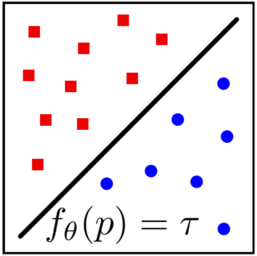
[Groueix et al., CVPR 2018]

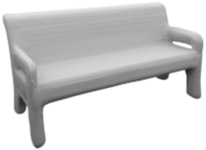


Learning-based 3D Reconstruction

This work:

- Implicit representation ⇒ **No discretization**
- Arbitrary topology & resolution
- Low memory footprint
- Not restricted to specific class





Occupancy Networks

Key Idea:

- Do not represent 3D shape explicitly

Occupancy Networks

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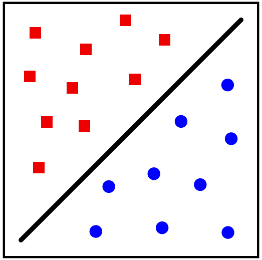
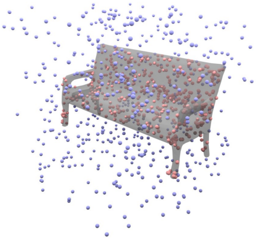
- Do not represent 3D shape explicitly
- Instead, consider surface **implicitly** as **decision boundary** of a non-linear classifier:

$$\underbrace{f_\theta : \mathbb{R}^3}_{\text{3D Location}} \times \underbrace{\mathcal{X}}_{\text{Condition (eg, Image)}} \rightarrow \underbrace{[0, 1]}_{\text{Occupancy Probability}}$$





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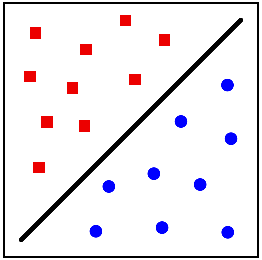
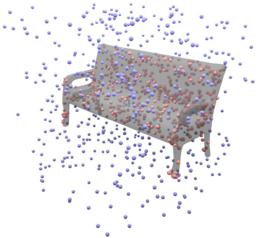
3D Location — Condition (eg, Image) — Occupancy Probability





Remarks:

- The function f_θ models an **occupancy field**

Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

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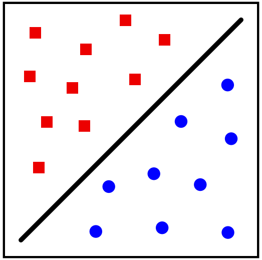
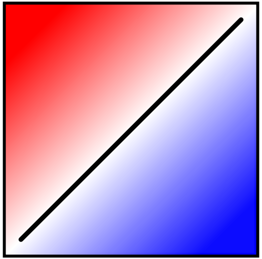
3D Location | Condition (eg, Image) | Occupancy Probability

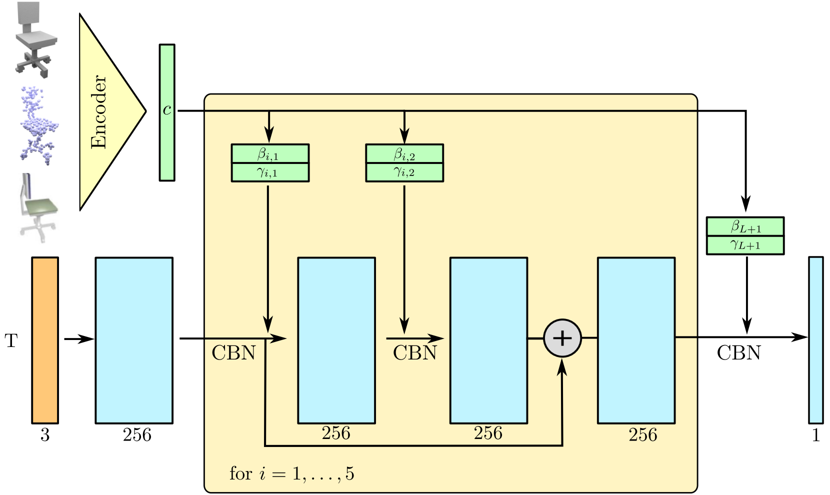




Remarks:

- The function f_θ models an **occupancy field**
- Also possible: **signed distance field** [Park et al., 2019]

Network Architecture



Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

Training Objective

Occupancy Network:

$$\mathcal{L}(\theta, \psi) = \sum_{j=1}^{K} \text{BCE}(f_\theta(p_{ij}, z_i), o_{ij})$$

- K: Randomly sampled 3D points ($K = 2048$)
- BCE: Cross-entropy loss

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Training Objective

Variational Occupancy Encoder:

$$\mathcal{L}(\theta, \psi) = \sum_{j=1}^{K} \text{BCE}(f_\theta(p_{ij}, z_i), o_{ij}) + KL\left[q_\psi(z|(p_{ij}, o_{ij})_{j=1:K}) \,\|\, p_0(z)\right]$$

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- BCE: Cross-entropy loss
- q_ψ: Encoder

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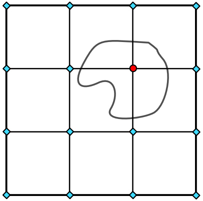
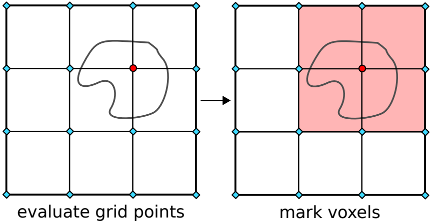
Occupancy Networks



Multiresolution IsoSurface Extraction (MISE):

- Build octree by incrementally querying the occupancy network

Occupancy Networks



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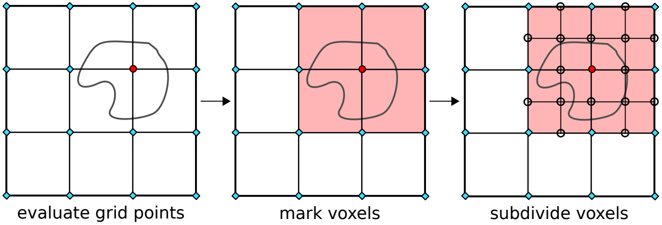

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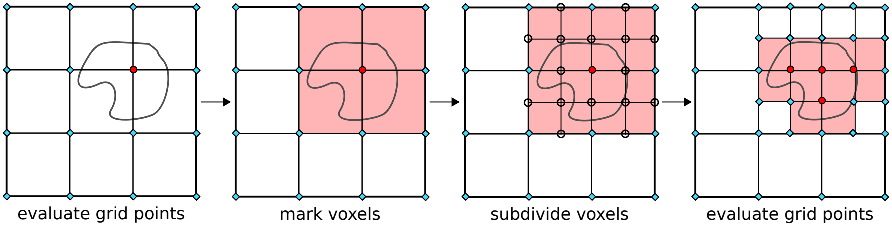

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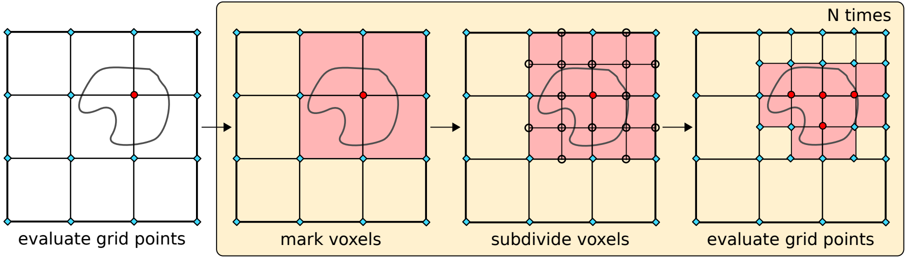

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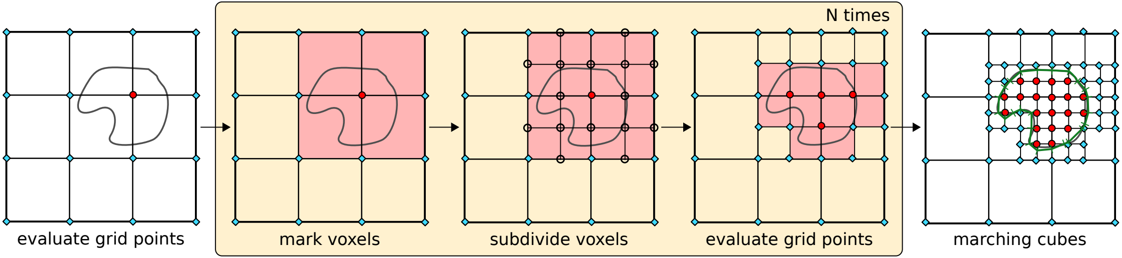
Occupancy Networks

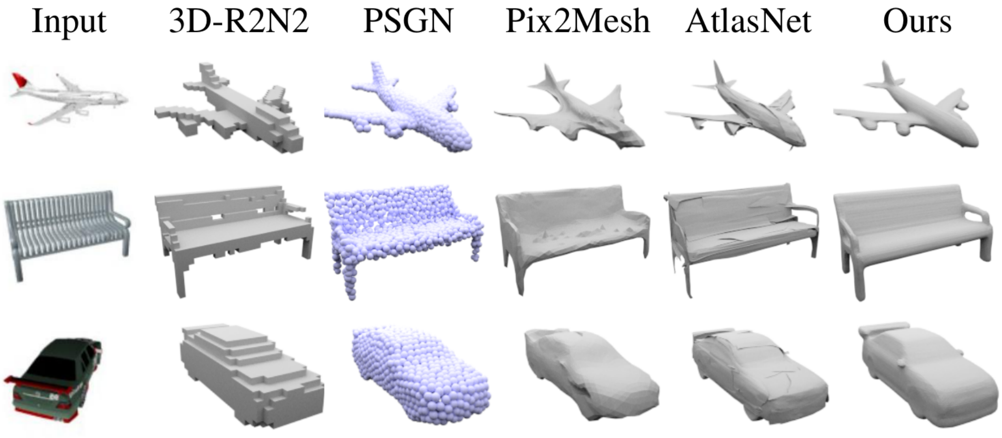


Multiresolution IsoSurface Extraction (MISE):

- Build octree by incrementally querying the occupancy network
- Extract triangular mesh using marching cubes algorithm (1-3 seconds in total)

Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

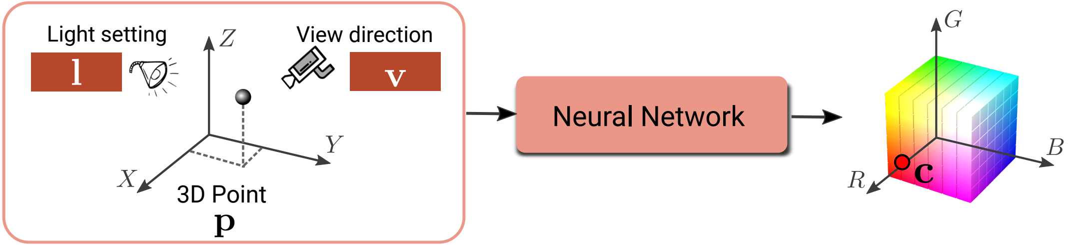
Results



Mescheder, Oechsle, Niemeyer, Nowozin and Geiger: Occupancy Networks: Learning 3D Reconstruction in Function Space. CVPR, 2019.

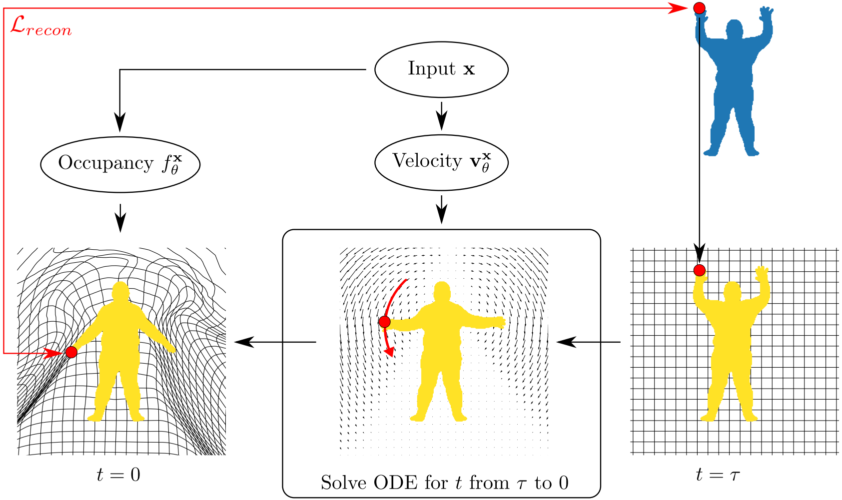
Applications

Appearance



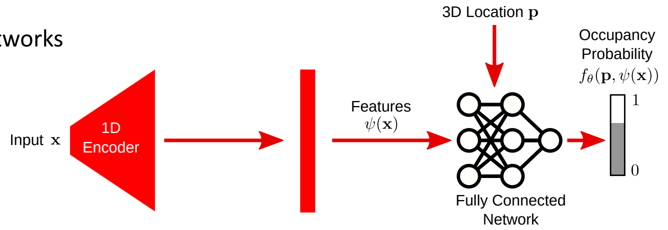
Light setting
l
Z
View direction
v
Y
X
3D Point
p
Neural Network
G
B
R
c

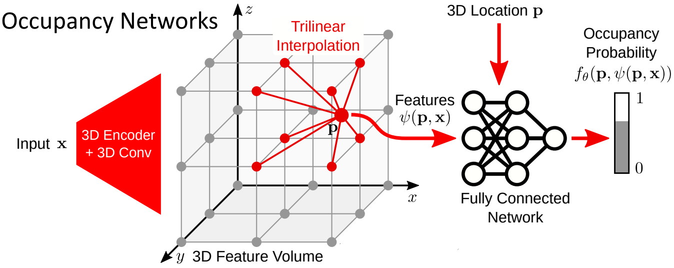
Motion



$\mathcal{L}_{recon}$
Input $\mathbf{x}$
Occupancy $f_\theta^{\mathbf{x}}$
Velocity $\mathbf{v}_\theta^{\mathbf{x}}$
$t = 0$
Solve ODE for t from τ to 0
$t = \tau$

3D Scenes

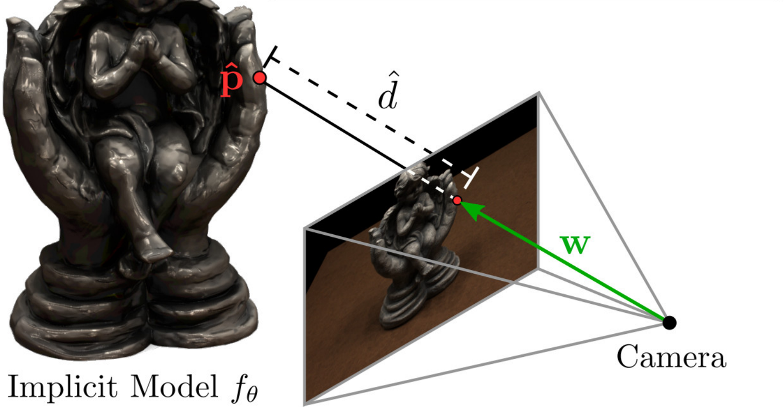




Peng, Niemeyer, Mescheder, Pollefeys and Geiger: Convolutional Occupancy Networks. ECCV, 2020.

Differentiable Rendering

$$\frac{\partial \hat{d}}{\partial \theta} = -\left(\frac{\partial f_\theta(\hat{\mathbf{p}})}{\partial \hat{\mathbf{p}}} \cdot \mathbf{w}\right)^{-1} \frac{\partial f_\theta(\hat{\mathbf{p}})}{\partial \theta}$$



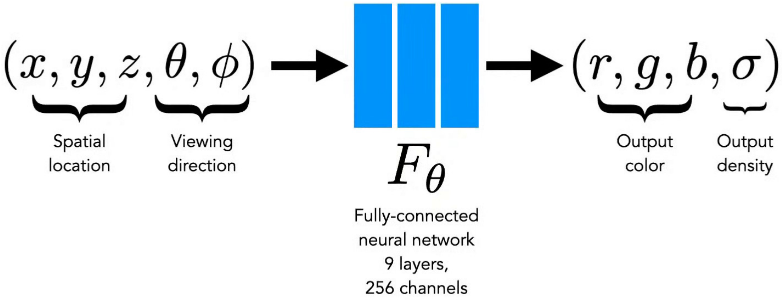
Neural Rendering: Neural Radiance Fields

Novel View Synthesis

- **Task:** Given a set of images of a scene (left), render image from novel viewpoint (right)

Mildenhall, Srinivasan, Tancik, Barron, Ramamoorthi and Ng: NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV, 2020.

NeRF: Representing Scenes as Neural Radiance Fields



- Vanilla **ReLU MLP** that maps from **location/view direction to color/density**
- **Density** σ describes how solid/transparent a 3D point is (can model, e.g., fog)
- Conditioning on view direction allows for modeling **view-dependent effects**

Volume Rendering

Rendering model for ray r(t) = o + td:

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

weights

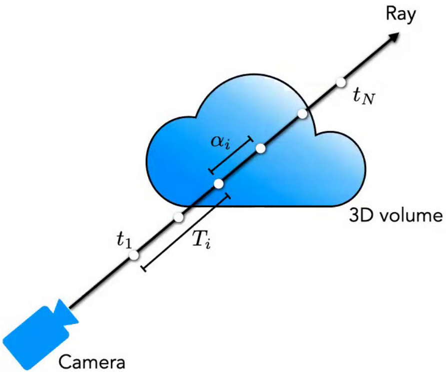
colors

How much light is blocked earlier along ray:

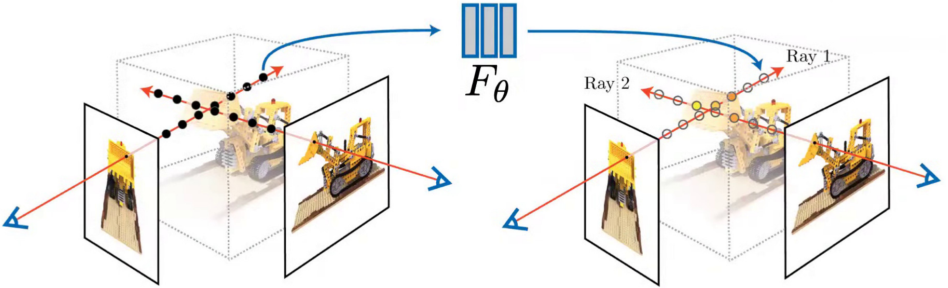
$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

How much light is contributed by ray segment *i*:

$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$



NeRF Training



$$\min_\theta \sum_i ||\,\text{render}_i(F_\theta) - I_i||^2$$

- Shoot ray, render ray to pixel, minimize **reconstruction error** via backpropagation

Mildenhall, Srinivasan, Tancik, Barron, Ramamoorthi and Ng: NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV, 2020.

Fourier Features

NeRF (Naive)

NeRF (with positional encoding)

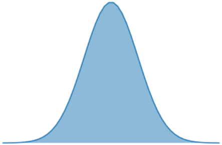
- Essential trick: Compute **positional encoding** for input point $\mathbf{x}$ and direction $\mathbf{d}$

Tancik et al.: Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains. NeurIPS, 2020.

Generative Neural Scene Representations

Generative Models

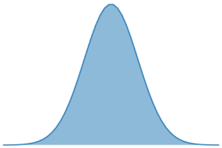
Sample a latent code from the prior distribution.



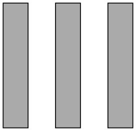
Latent Code

Generative Models

Pass latent code to trained generator G_θ.



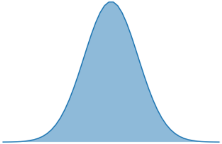
Latent Code



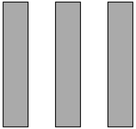
Generator G_θ

Generative Models

The generator outputs a synthesized image.



Latent Code



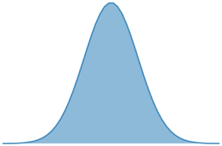
Generator G_θ

Generated Image*

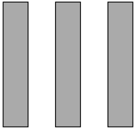
* The generated images are samples from StyleGAN2.

Generative Models

Sample more latent codes to get different generated images.



Latent Code



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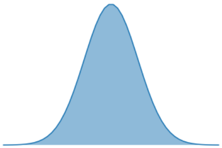

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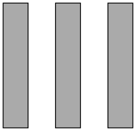

Generator G_θ

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Is the ability to sample photorealistic images
all we want?

Generative Models

For many applications, we require **control over the generation process**:

Generative Models

For many applications, we require **control over the generation process**:

Note: This and the following videos are only shown when opened with a supported PDF reader (e.g. Okular).

Animation Movies

Video Source: Disney's Toy Story 4 Trailer

Generative Models

For many applications, we require **control over the generation process**:

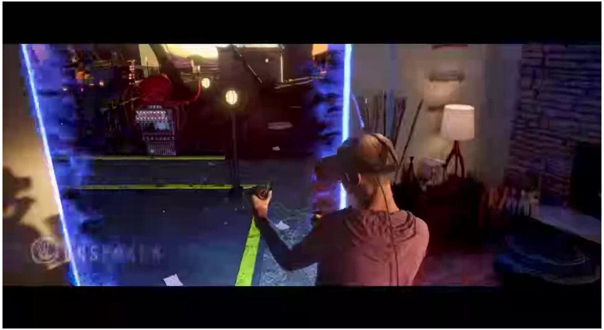
Video Games

Video Source: Gran Turismo 7 Trailer

Generative Models

For many applications, we require **control over the generation process**:

Virtual Reality



Video Source:Oculus Rift Trailer

Generative Models

Goal: A generative model for **3D-aware image synthesis** which allows us to:

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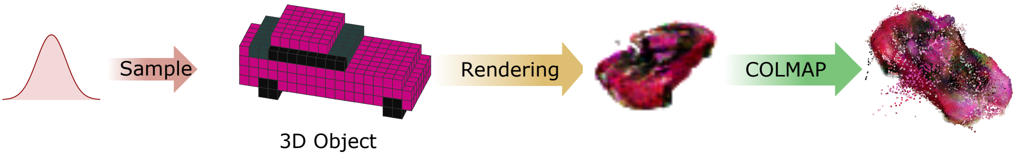
Goal: A generative model for **3D-aware image synthesis** which allows us to:

- Generate photorealistic images
- Control individual objects wrt. their pose, size, and position in 3D
- Control camera viewpoint in 3D
- Train from collections of unposed images

What representation should we use for 3D-aware image synthesis?

3D Representations

Voxel-based 3D Shape with Volumetric Rendering



PlatonicGAN [Henzler et al., ICCV 2019]

3D Representations

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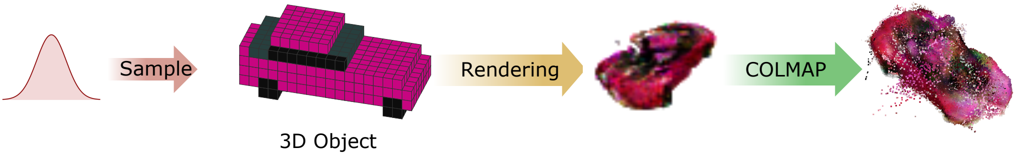

PlatonicGAN [Henzler et al., ICCV 2019]

+ Multi-view consistent

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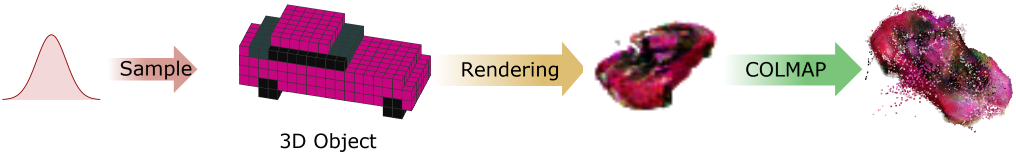


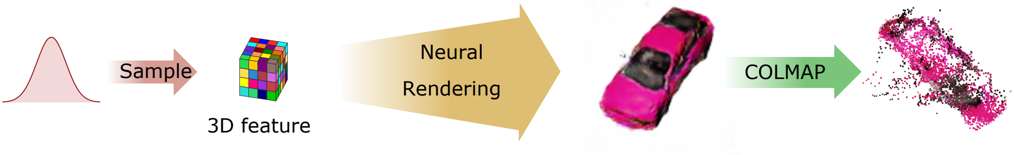
PlatonicGAN [Henzler et al., ICCV 2019]

+ Multi-view consistent

− Low image fidelity, high memory consumption

3D Representations

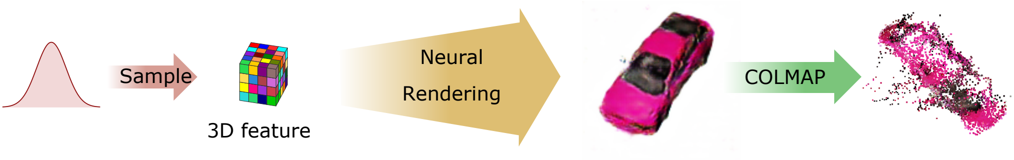
Voxel-based 3D Latent Feature with Learnable Projection



HoloGAN [Nguyen-Phuoc et al., ICCV 2019]

3D Representations

Voxel-based 3D Latent Feature with Learnable Projection



HoloGAN [Nguyen-Phuoc et al., ICCV 2019]

+ High image fidelity

Schwarz, Liao, Niemeyer, Geiger: GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis. NeurIPS, 2020

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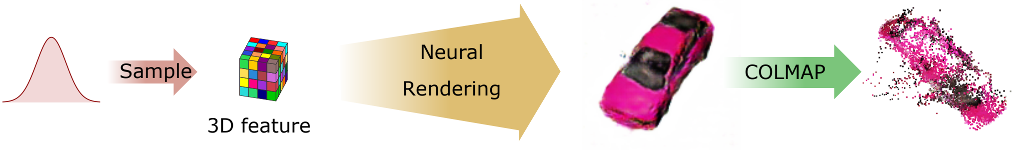


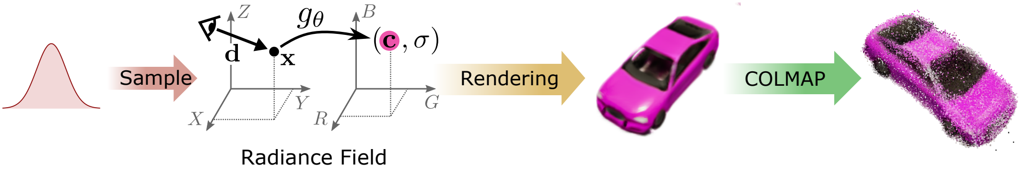
HoloGAN [Nguyen-Phuoc et al., ICCV 2019]

+ High image fidelity

− Object identity may vary with viewpoint due to learnable projection

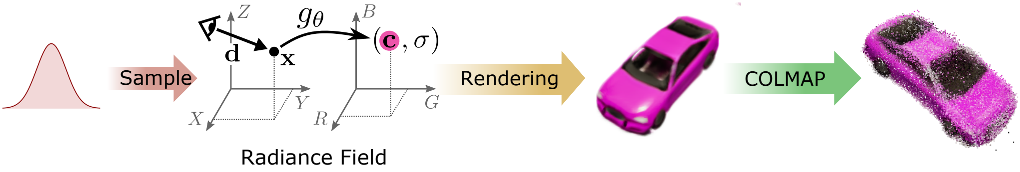
3D Representations

Generative Radiance Fields



3D Representations

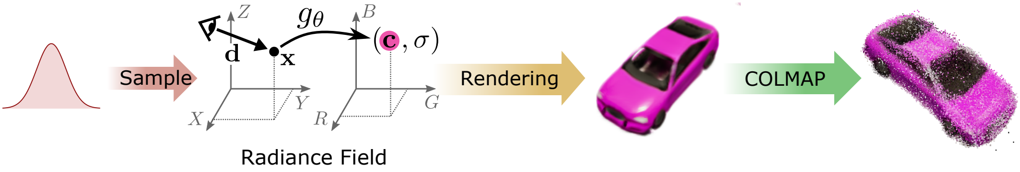
Generative Radiance Fields



+ Continuous representation, multi-view consistent

3D Representations

Generative Radiance Fields



- Continuous representation, multi-view consistent
- High image fidelity, low memory consumption

Schwarz, Liao, Niemeyer, Geiger: GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis. NeurIPS, 2020

Generative Radiance Fields

Generative Radiance Fields

Sample camera matrix $\mathbf{K}$, camera pose $\boldsymbol{\xi} \sim p_\xi$, and patch sampling pattern $\boldsymbol{\nu} \sim p_\nu$.

$\mathbf{K}$

$\boldsymbol{\xi} \sim p_\xi$

$\boldsymbol{\nu} \sim p_\nu$

Schwarz, Liao, Niemeyer, Geiger: GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis. NeurIPS, 2020

Generative Radiance Fields

Pass $\mathbf{K}$, $\boldsymbol{\xi}$, and $\boldsymbol{\nu}$ to generator G_θ and sample pixels / rays on image plane.

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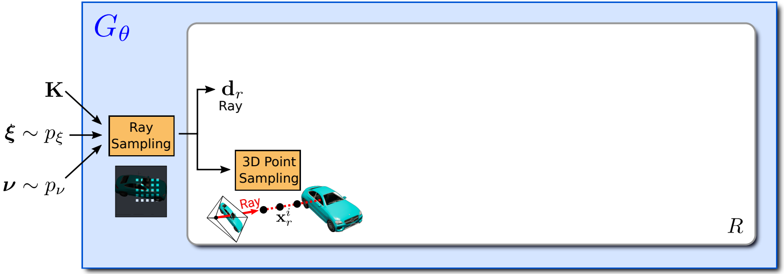
Generative Radiance Fields

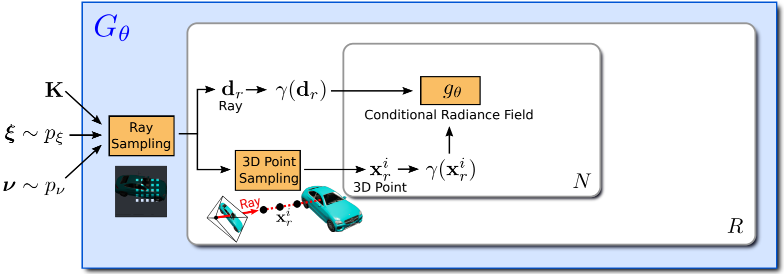
For each ray, get viewing direction $\mathbf{d}_r$ and sample 3D points $\mathbf{x}_r^i$ along ray.



Patch Generator

Generative Radiance Fields

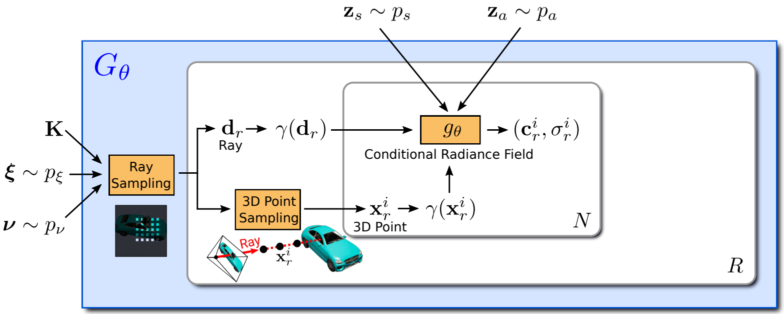
Pass $\mathbf{d}_r$ and $\mathbf{x}_r^i$ to positional encoding γ and then to the conditional radiance field g_θ.



Patch Generator

Generative Radiance Fields

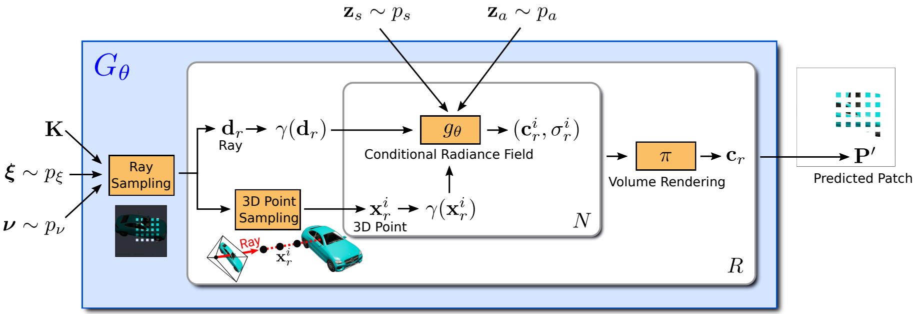
Sample latent shape and appearance codes $\mathbf{z}_s, \mathbf{z}_a$ and pass them to g_θ.



Patch Generator

Generative Radiance Fields

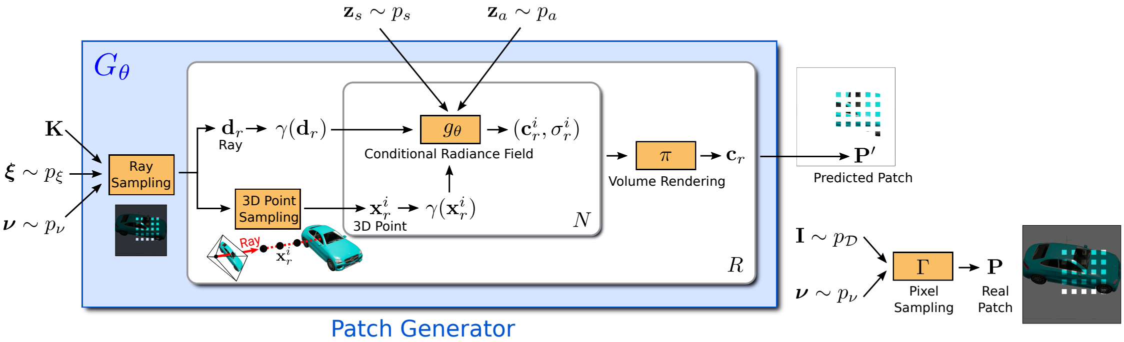
Perform volume-rendering for each ray and get predicted patch $\mathbf{P}'$.



Patch Generator

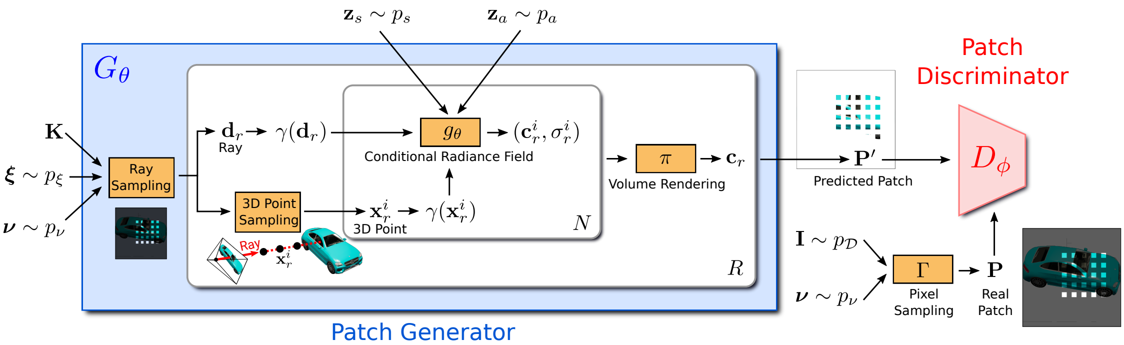
Generative Radiance Fields

Sample patch $\mathbf{P}$ from real image $\mathbf{I}$ drawn from the data distribution $p_{\mathcal{D}}$.



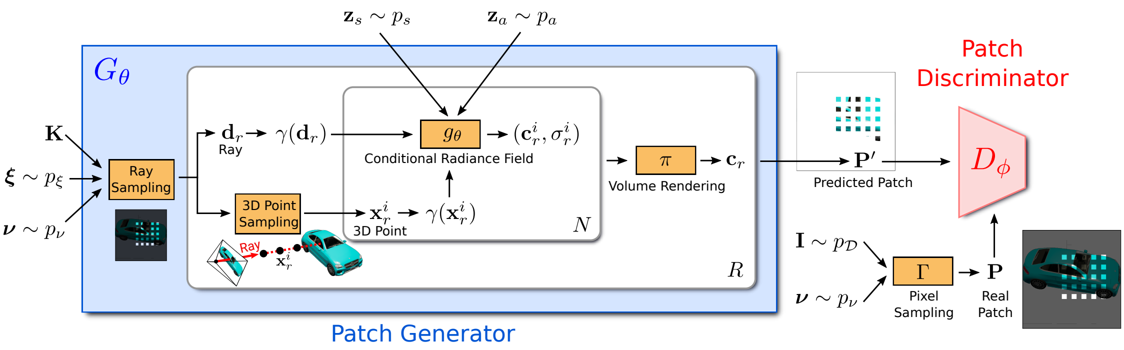
Generative Radiance Fields

Pass fake and real patch $\mathbf{P}', \mathbf{P}$ to discriminator D_ϕ and train with adversarial loss.



Schwarz, Liao, Niemeyer, Geiger: GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis. NeurIPS, 2020

Generative Radiance Fields



- Generator/discriminator for **image patches** of size 32×32 pixels
- Patches sampled at **random scale** using dilation

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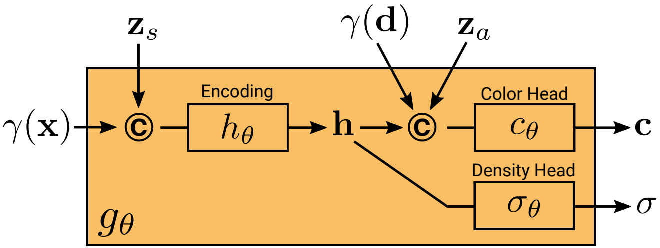
How do we parametrize

Conditional Radiance Fields?

Conditional Radiance Fields

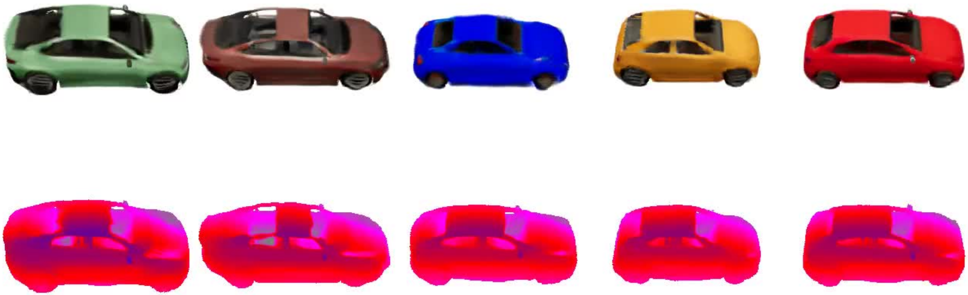


- Conditional radiance fields as fully-connected MLPs with ReLU activation
- Shape code $\mathbf{z}_s$ concatenated with encoded 3D location $\gamma(\mathbf{x})$
- Appearance code $\mathbf{z}_a$ concatenated with encoded viewing direction $\gamma(\mathbf{d})$

How well does it work?

Generative Radiance Fields

Results on synthetic Carla dataset at 256^2 pixels:



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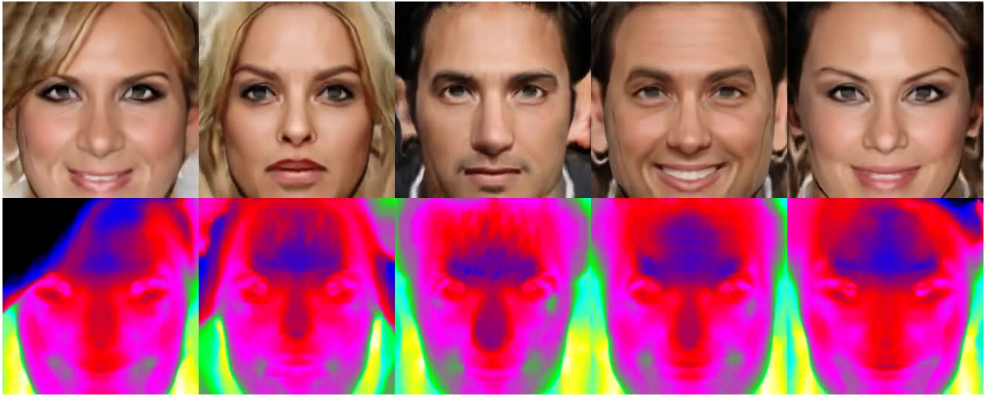
Generative Radiance Fields

Results on real CelebA-HQ dataset at 256^2 pixels:



Schwarz, Liao, Niemeyer, Geiger: GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis. NeurIPS, 2020

How can we scale to
more complex, multi-object scenes?

GIRAFFE: Compositional Generative Neural Feature Fields

GRAF:

- Incorporate a **3D representation** into the generative model

GIRAFFE: Compositional Generative Neural Feature Fields

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GIRAFFE: Compositional Generative Neural Feature Fields

GRAF:

- Incorporate a **3D representation** into the generative model

GIRAFFE:

- Incorporate a **compositional 3D scene representation** into the generative model
- Incorporate a **neural renderer** to yield fast and high-quality inference

Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

GIRAFFE

Sample N shape and appearance codes.

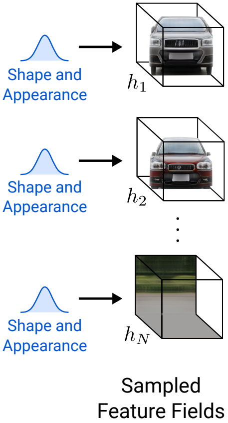
Shape and
Appearance

Shape and
Appearance

Shape and
Appearance

GIRAFFE

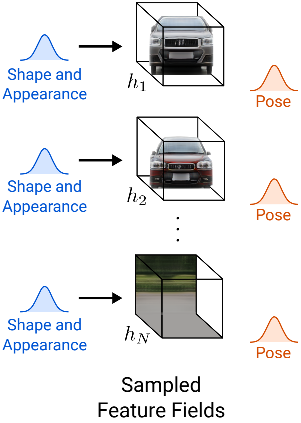
Get N feature fields. Note: We show features in RGB color for clarity.



Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

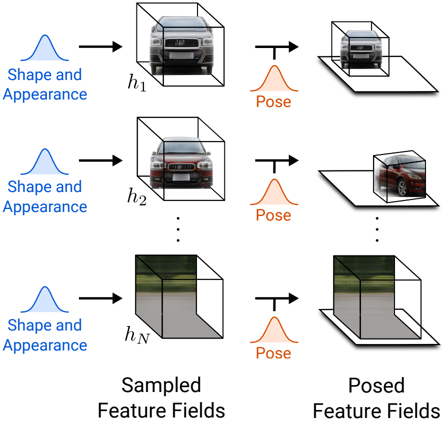
GIRAFFE

Sample size and pose for each feature field.



GIRAFFE

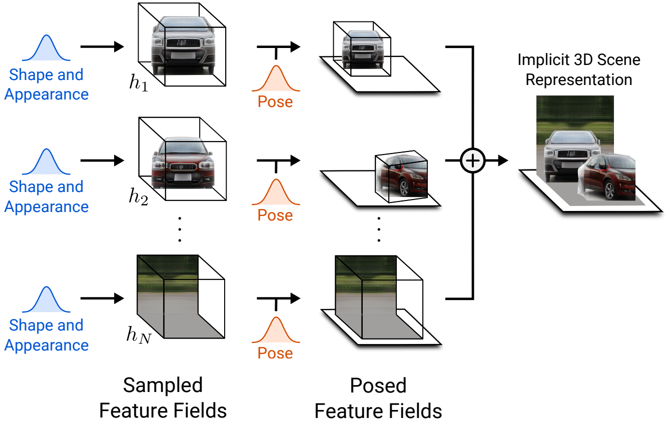
Get posed feature fields.



Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

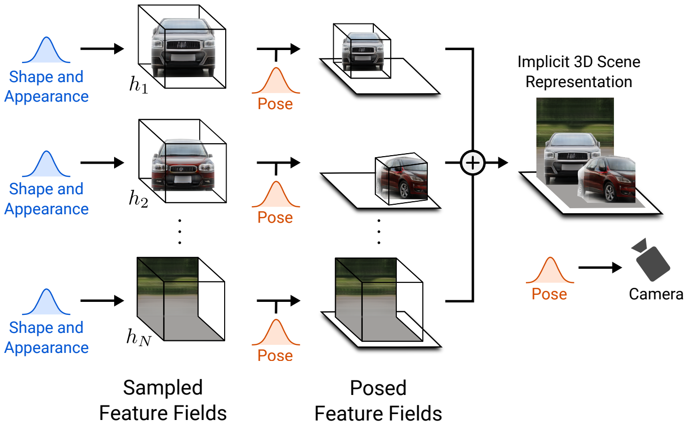
Composite all feature feature fields to one 3D scene representation.



Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

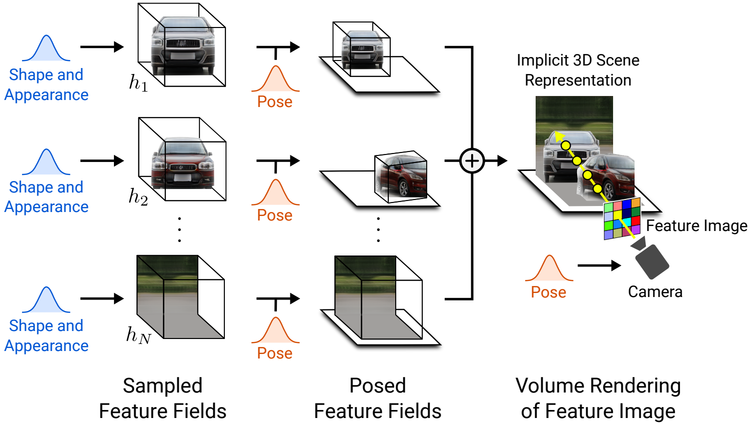
Sample a camera pose.



Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

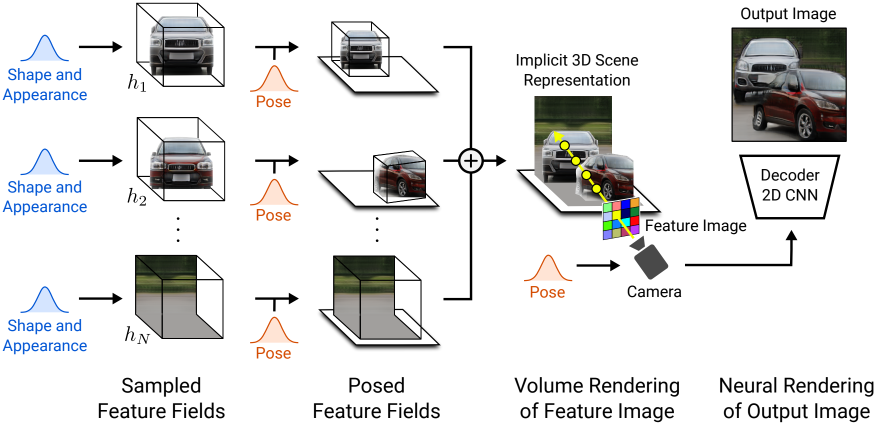
Perform volume rendering and get feature image.



Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

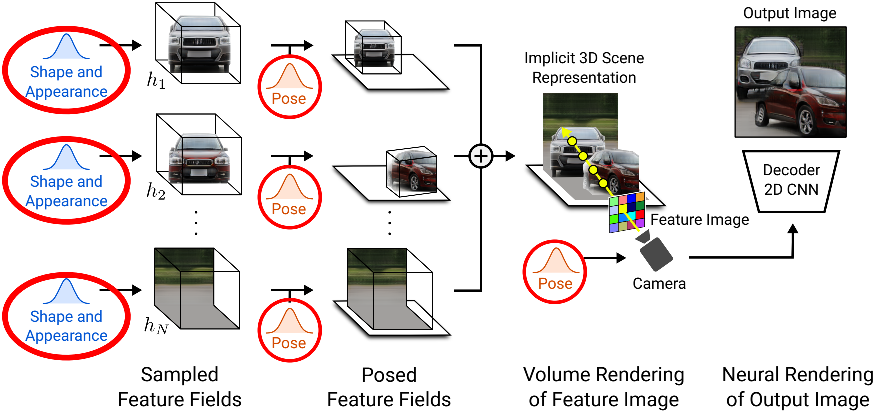
Pass feature image to neural renderer to obtain final output.



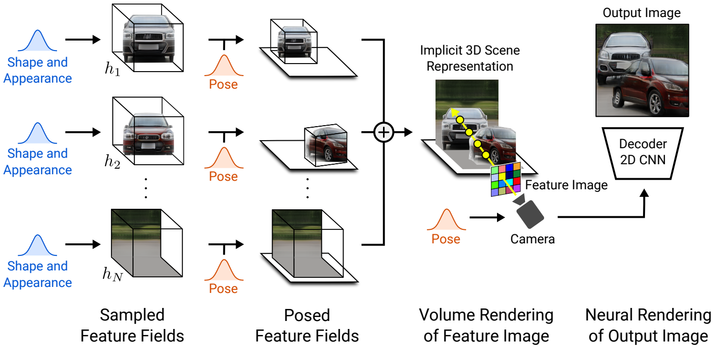
Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

GIRAFFE

At test time, we can sample individual codes and **control the poses**.



GIRAFFE



- We train with adversarial loss **on full image**
- We volume-render the feature image at 16×16 pixels

How well does it work?

GIRAFFE

We compare object translation for a 2D-based GAN (left) and our method (right):

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GIRAFFE

We can perform more complex operations like circular translations

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GIRAFFE

We can add more objects at test time (trained on two-object)

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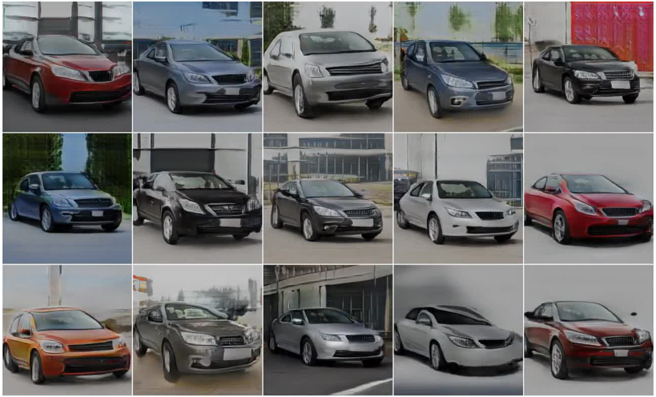
GIRAFFE

We can rotate the object



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GIRAFFE

We can translate the object

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GIRAFFE

We can change the object shape

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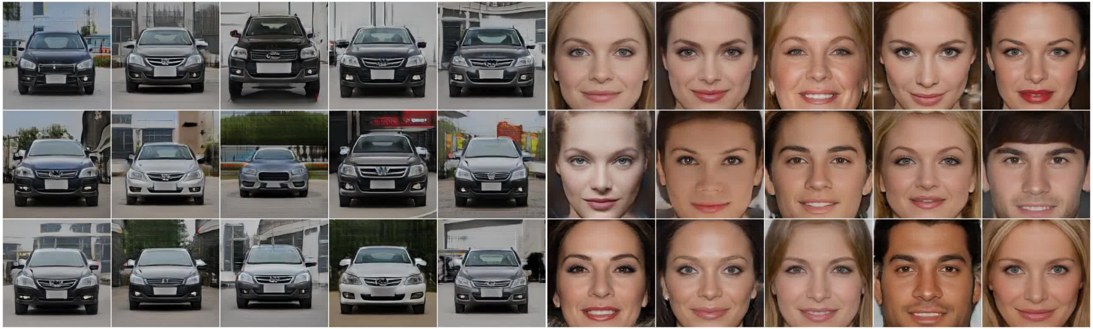
GIRAFFE

We can change the object appearance



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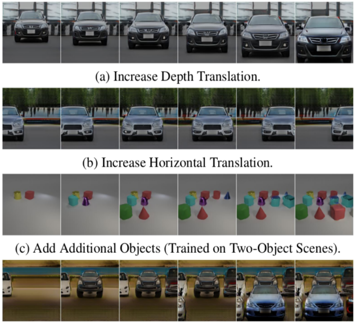
GIRAFFE

We can generate out-of-distribution samples



(a) Increase Depth Translation.

(b) Increase Horizontal Translation.

(c) Add Additional Objects (Trained on Two-Object Scenes).

(d) Add Additional Objects (Trained on Single-Object Scenes).

Summary

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Niemeyer, Geiger: GIRAFFE: Representing Scenes as Compositional Generative Neural Feature Fields. CVPR, 2021

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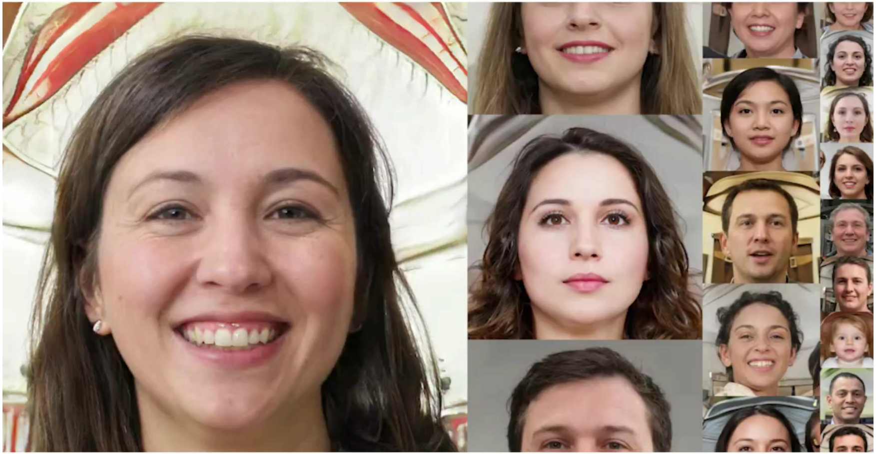
- GIRAFFE: Generative Model of **complex, multi-object scenes**

Summary

This research is very activate and leads to state-of-the-art results:



Gu, Jiatao, et al. "StyleNeRF: A Style-based 3D-Aware Generator for High-resolution Image Synthesis." arXiv preprint arXiv:2110.08985 (2021).

Thank you!