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# **IMPLICIT NEURAL REPRESENTATION AND UNIFIED IMPLICIT NEURAL STYLIZATION**

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# Why Go Implicit?

Image(2D, **discrete**)



Mesh(3D, **discrete**)



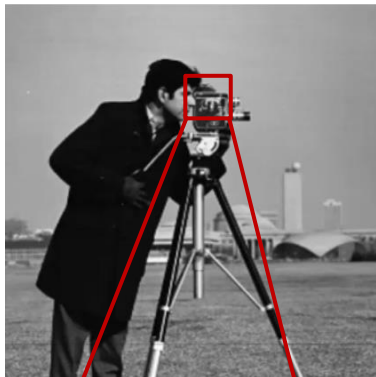
Audio(**discrete**)



If images weren't discrete grids, would we use CNN today?  
How to go infinite resolution for representing signals?

# Why Go Implicit?

Image(2D, **discrete**)



Mesh(3D, **discrete**)



Audio(**discrete**)



# Why Go Implicit?



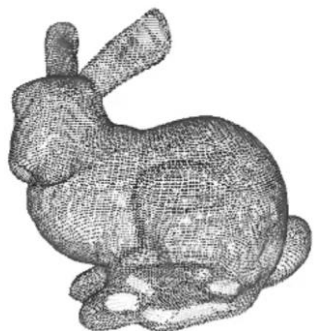
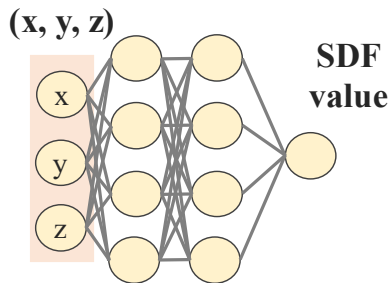
Input (360px)

Pixels

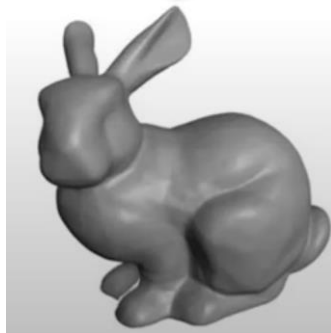
Bilinear Interpolation

Implicit-based <sup>[1]</sup>

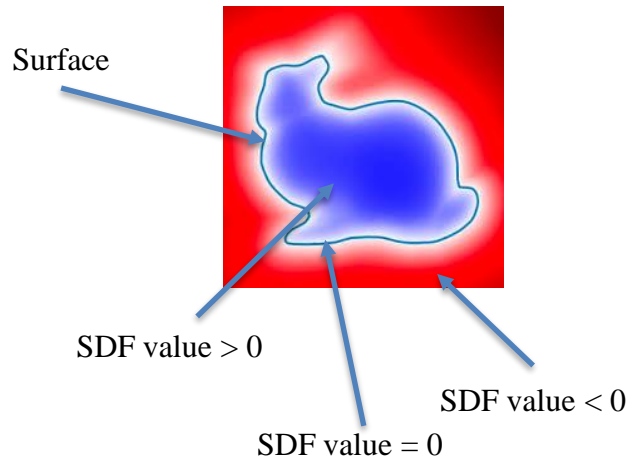
# Benefits (e.g., Signed Distance Function-SDF)



Discrete Representation



Continuous Representation



## Benefits:

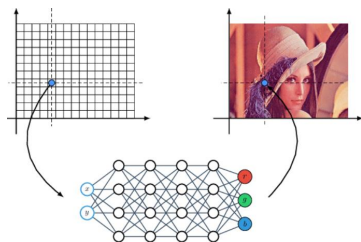
- Agnostic to the resolution
- Model memory scales with signal complexity

# Categories

## Image Fitting(SIREN)

(Sitzmann et al, 2020 <sup>[1]</sup>)

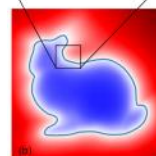
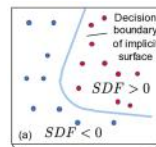
$(x, y) \rightarrow \text{pixel intensity}$



## Deep SDF

(Park et al, 2019 <sup>[2]</sup>)

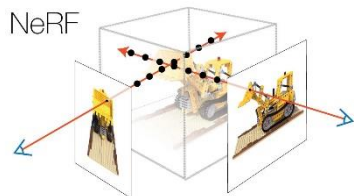
$(x, y, z) \rightarrow \text{distance}$



## Neural Radiance Field

(Ben et al, 2020 <sup>[3]</sup>)

$(x, y, z) \rightarrow (\text{color}, \text{density})$



## Scene Representation Network

(Sitzmann et al, 2019 <sup>[3]</sup>)

$(x, y, z) \rightarrow \text{latent vector (color, dist)}$



[1] Sitzmann et al., Implicit Neural Representations with Periodic Activation Functions

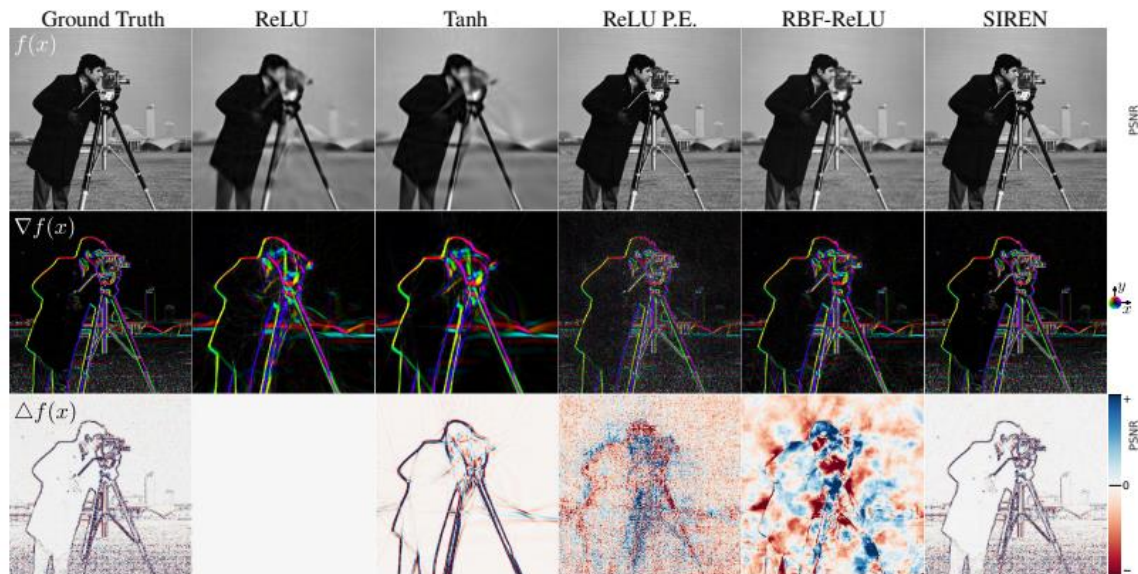
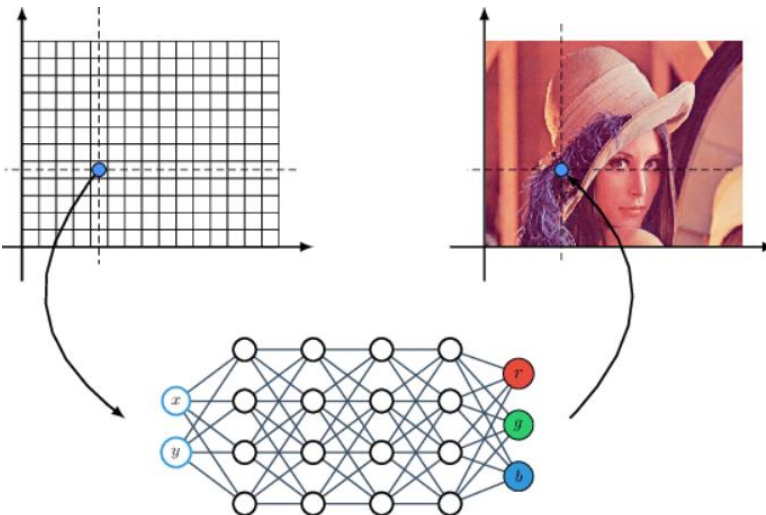
[2] Park et al., DeepSDF: Learning continuous signed distance functions for shape representation

[3] Ben et al., Representing Scenes as Neural Radiance Fields for View Synthesis

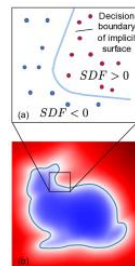
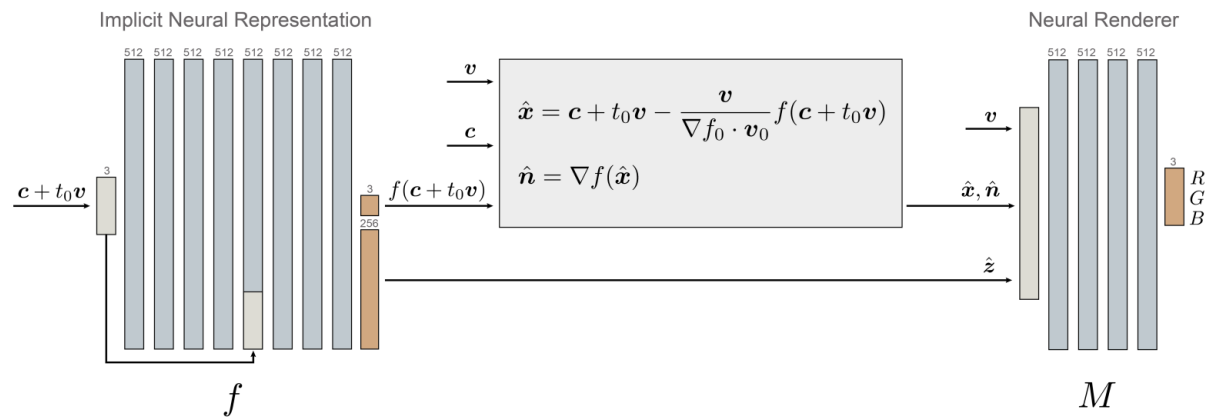
[4] Sitzmann et al., Scene representation networks: Continuous 3d-structure-aware neural scene representations



# INR (Image Fitting)



# INR (Signed Distance Function/SDF)



$(x, y, z) \rightarrow \text{distance}$



# INR (Neural Radiance Fields/NeRF)

Input Images



Optimize NeRF

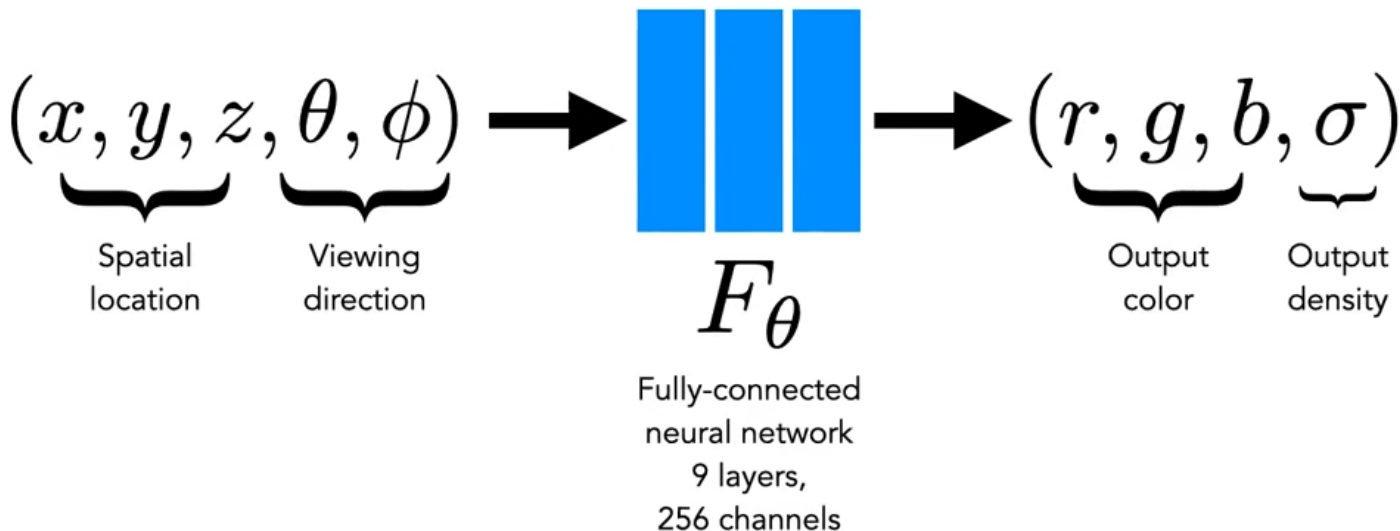


Render new views



Neural Radiance Field

# INR (Neural Radiance Fields/NeRF)



# NeRF Preliminary: Volume Rendering

Rendering model for ray  $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ :

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

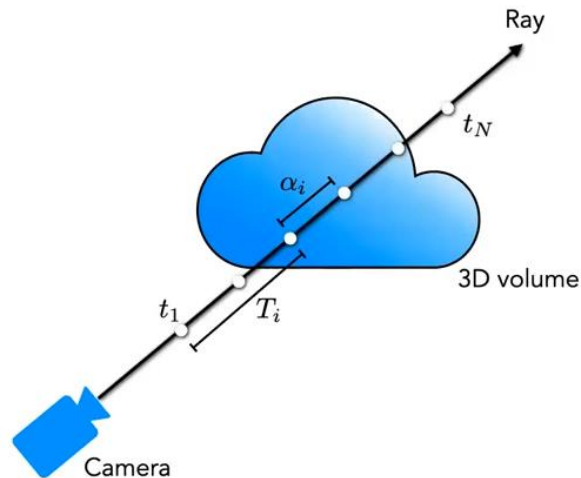
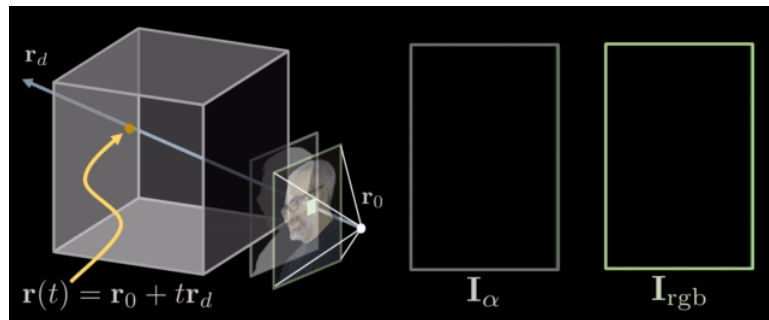
↑ weights
 ↑ colors

How much light is blocked earlier along ray:

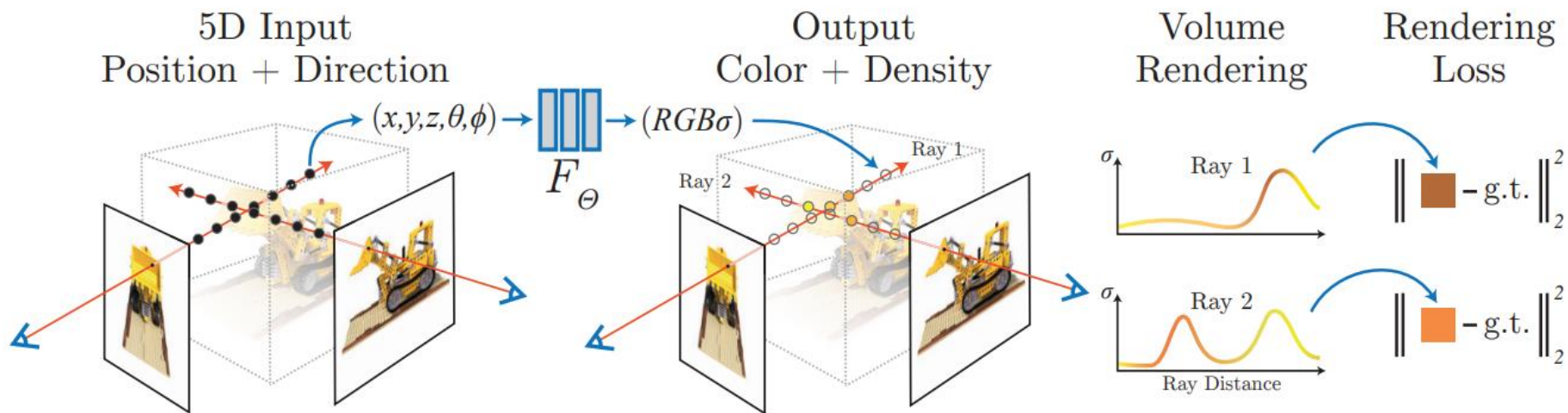
$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

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

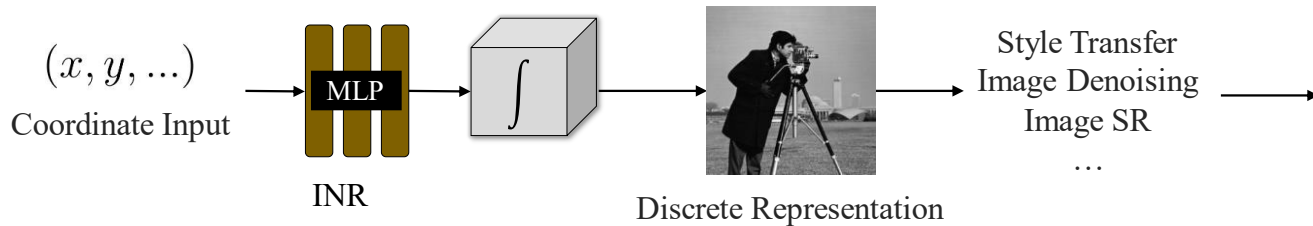
$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$



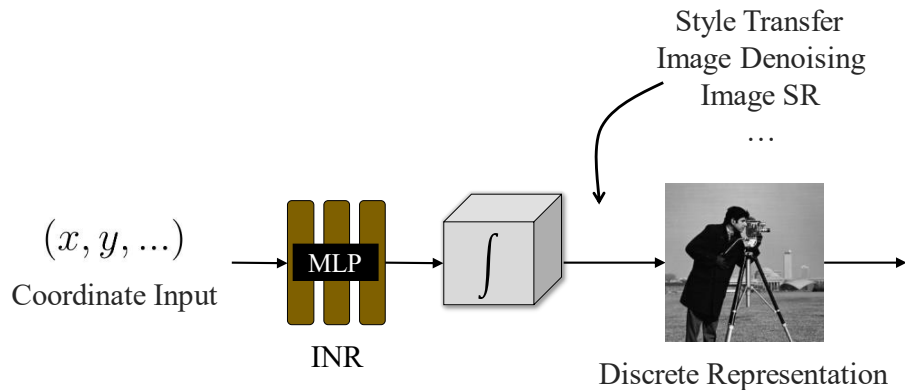
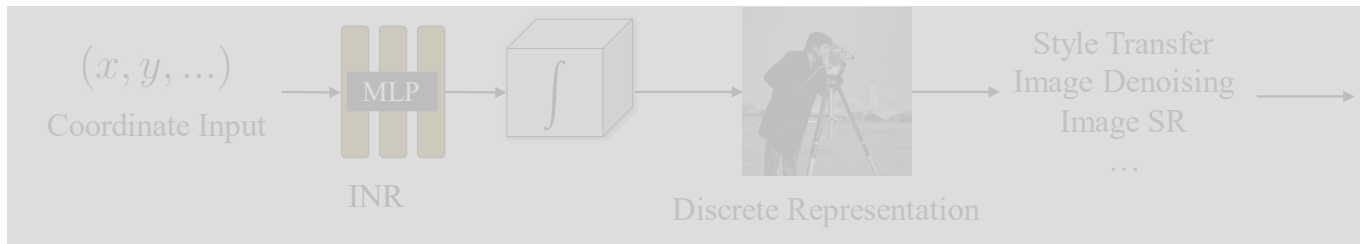
# NeRF: Training Pipeline



# Question: How to Edit INR?



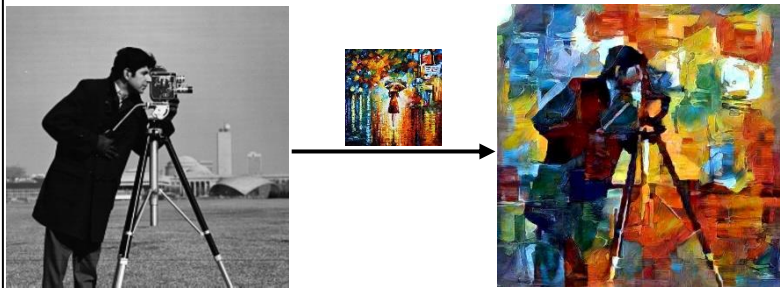
# Question: How to Edit INR?





# Unified Implicit Neural Stylization (INS)

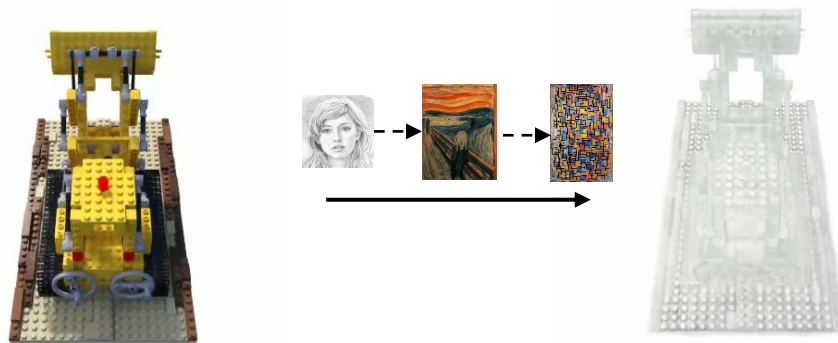
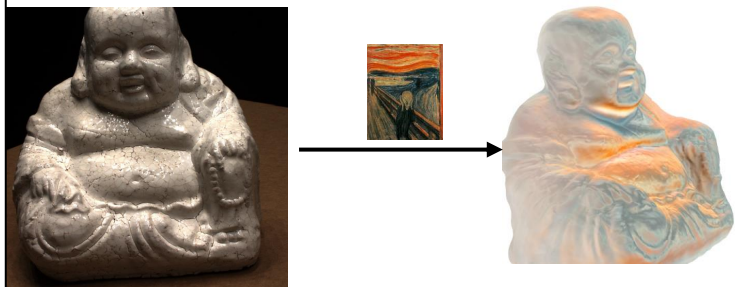
## Image Fitting



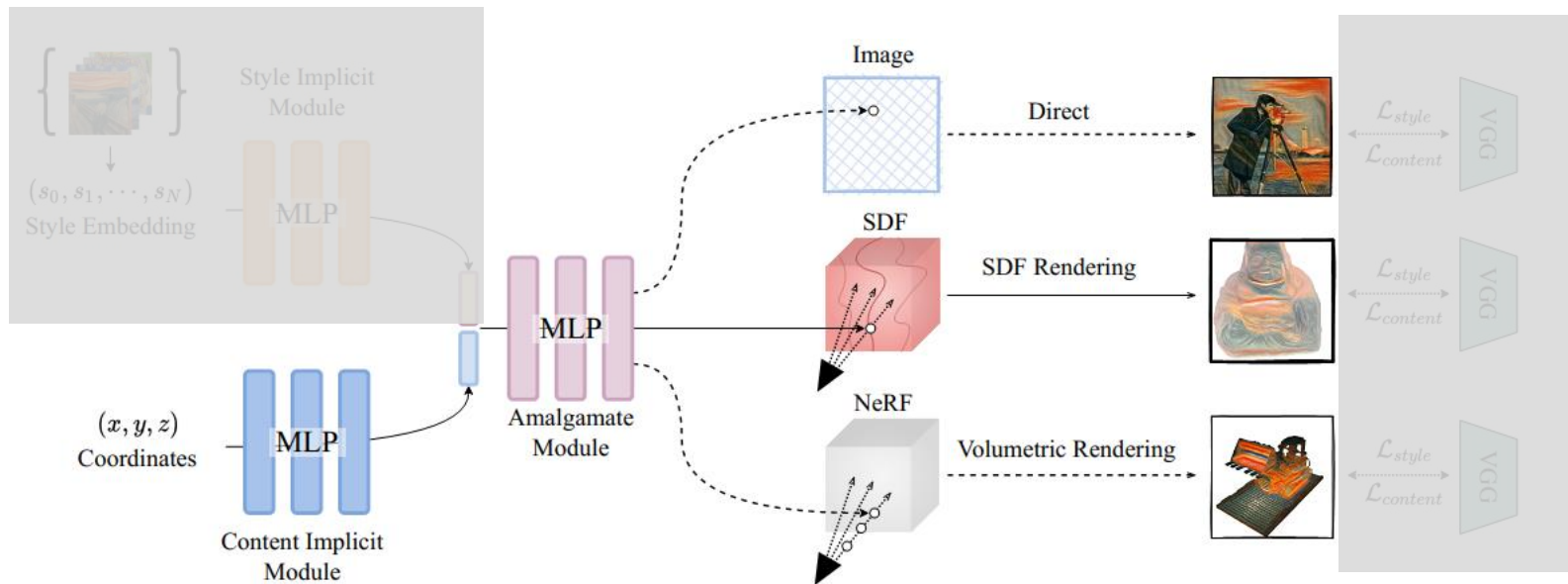
## Neural Radiance Field



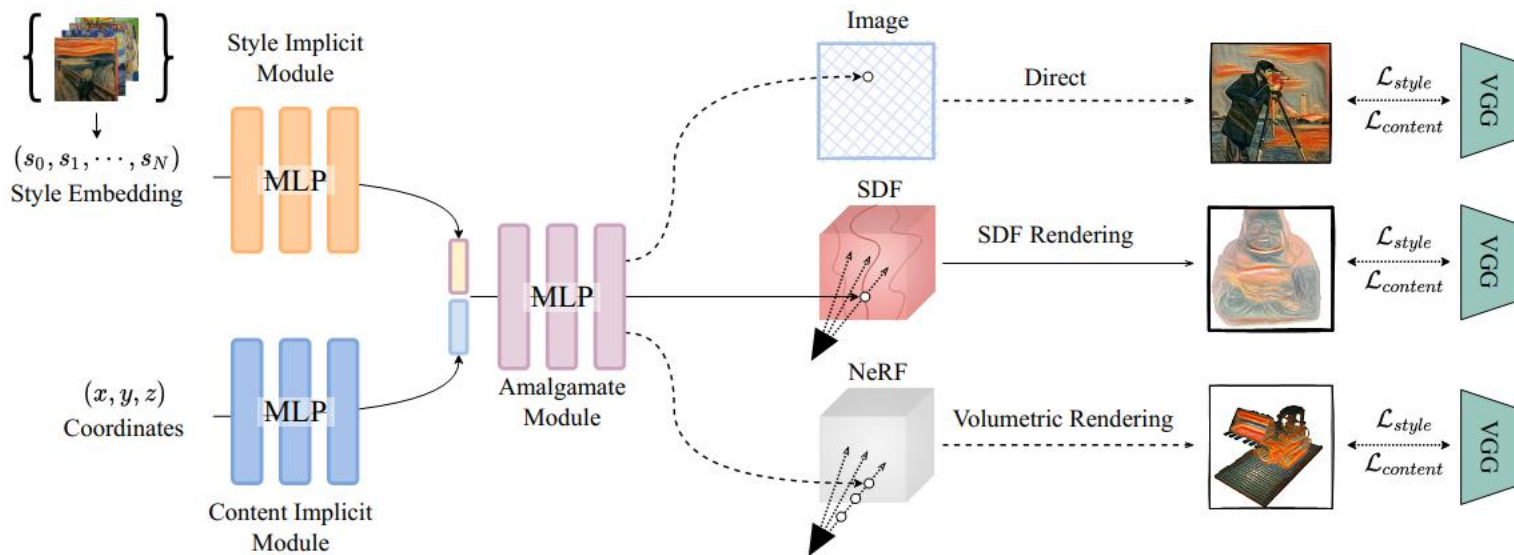
## Signed Distance Function



# INS Framework



# INS Framework



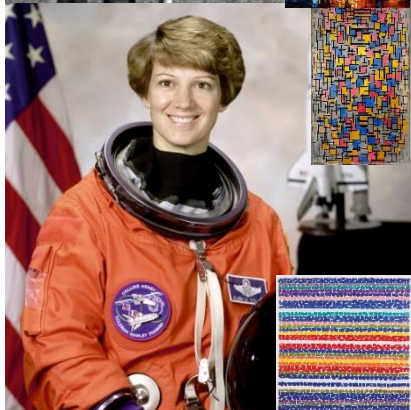
Inputs: implicit coordinates, ray directions and style embeddings.

Style Implicit Module (SIM) and Content Implicit Module (CIM) are used to extract conditional implicit style features and implicit scene features.

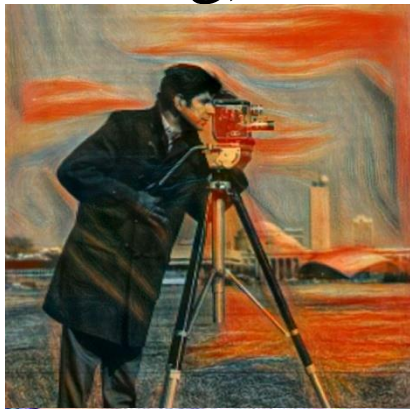
Amalgamate Module (AM) is applied to fuse features, generating stylized density and color intensity of each 3D point.

An implicit rendering step is applied on the top of AM to render the pixel intensity.

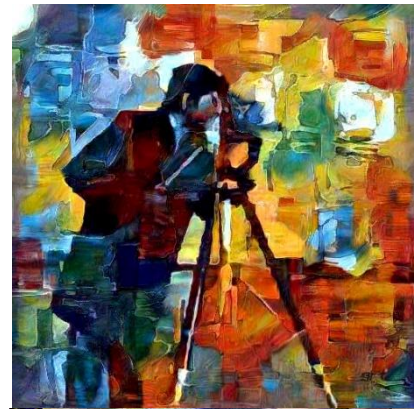
# INS Results (Image Fitting)



Content+Style Image



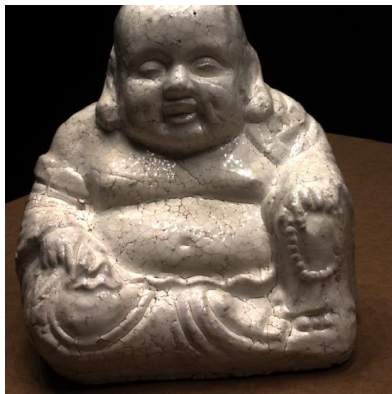
Stylized Image



Stylized Image



# INS Results (SDF)

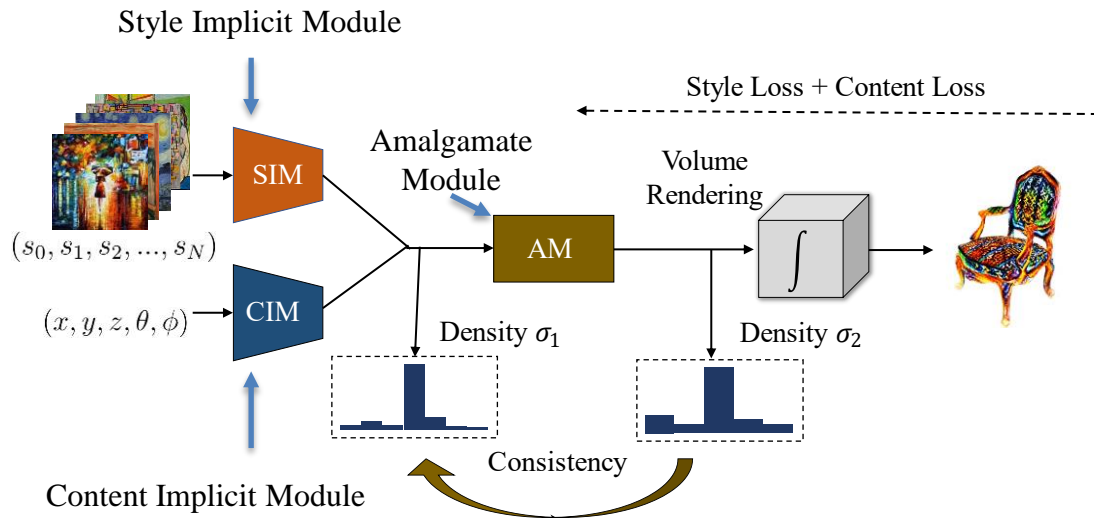


Content Image (1 view)

Stylize Image

Stylized Image

# INS Framework (NeRF)



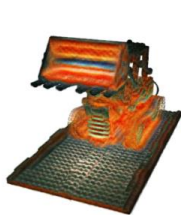
The proposed self-distilled geometry consistency. The CIM weights in the grey box are from a pre-trained NeRF and are kept fixed since then. During fine-tuning, the output density of the fixed CIM serves as geometry constraints for the stylized density from the output of AM.



# INS Framework (NeRF)



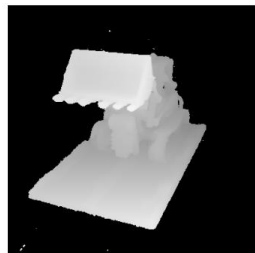
Color Image



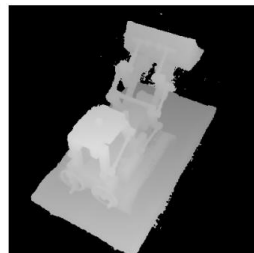
Color w/ GC



Color w/ GC



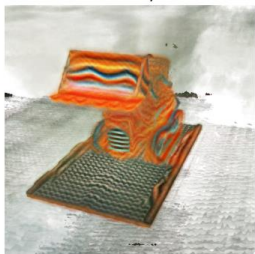
Depth w/ GC



Depth w/ GC



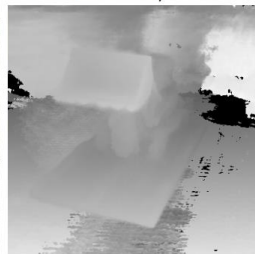
Style Image



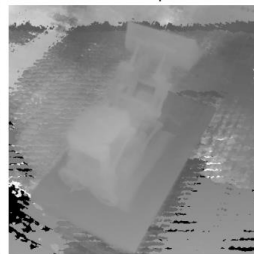
Color w/o GC



Color w/o GC



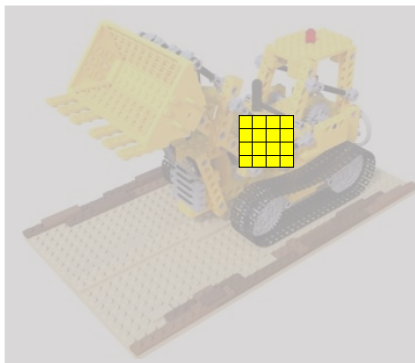
Depth w/o GC



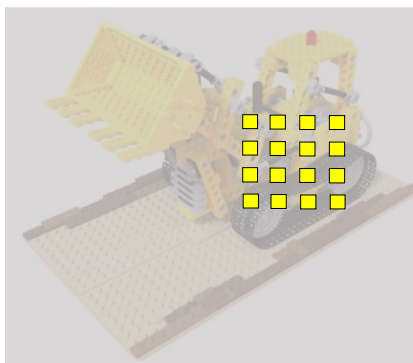
Depth w/o GC

Qualitative results of the self-distilled geometry consistency(“GC”). Both the rendered images and depth maps are shown to validate the effectiveness of the proposed consistency.

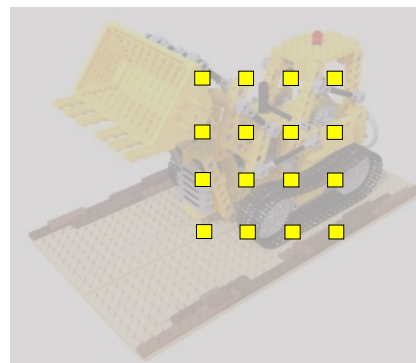
# INS Framework (NeRF)



Sampling Stride = 1



Sampling Stride = 2



Sampling Stride = 4



Color Image



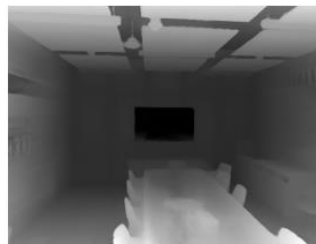
Style



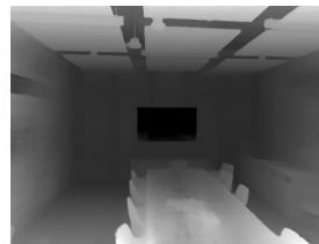
Color w/ SS



Color w/o SS



Depth w/ SS



Depth w/o SS

# INS Results (NeRF)



Content Image

Stylize Image

Stylization

# INS Results (NeRF)



Content Image

Stylize Image

Stylization



# INS Results (NeRF)



Content Image

Stylize Image

Stylization

# INS Results (NeRF Style Interpolation)





# INS Results (NeRF Comparisons)



Content Scene and Style Image

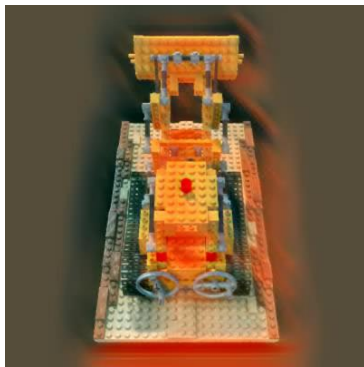


Ours



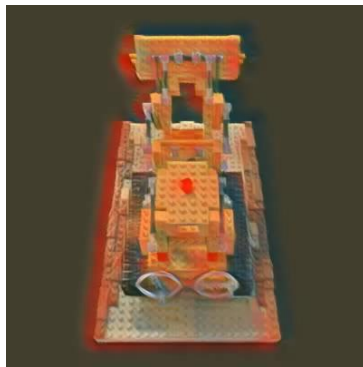
Style3D

[Chiang et.al, 2021]



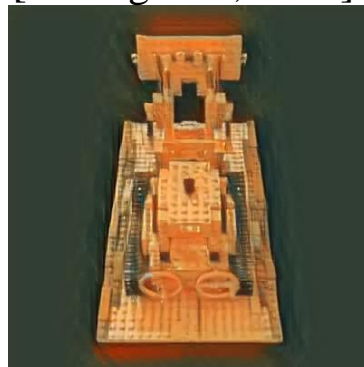
Perceptual

[Xun et.al, 2017]



MCCNet

[Deng et.al, 2021]



ReReVST

[Wang et.al, 2020]

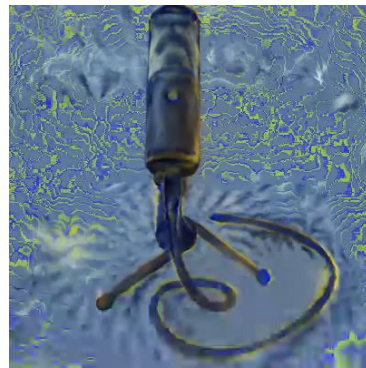
# INS Results (NeRF Comparisons)



Content Scene and Style Image

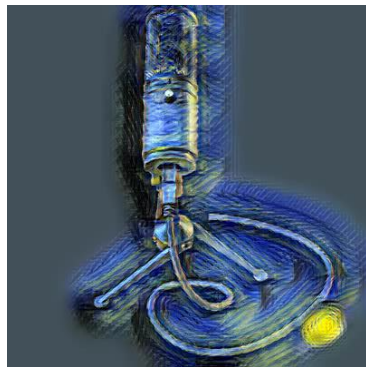


Ours



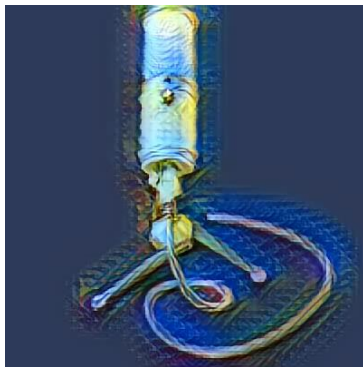
Style3D

[Chiang et.al, 2021]



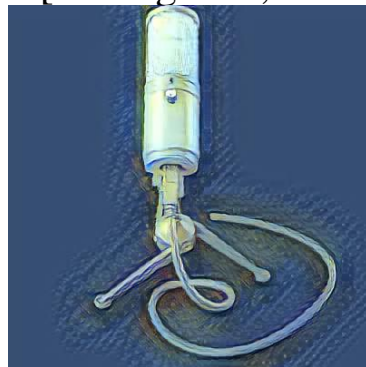
Perceptual

[Xun et.al, 2017]



MCCNet

[Deng et.al, 2021]



ReReVST

[Wang et.al, 2020]

# INS Results (NeRF Comparisons)



Content Scene and Style Image



Ours



Style3D

[Chiang et.al, 2021]



Perceptual

[Xun et.al, 2017]



MCCNet

[Deng et.al, 2021]



ReReVST

[Wang et.al, 2020]

# Conclusion



- Implicit Neural Representation (INR), a better continuous representation for small scale object/scene.
- We can edit INR on the feature domain to preserve its continuity.



- Implicit Neural Representation (INR) typically requires per-scene training, which is not very generalizable.



# What's Next

- NeRF for dynamic scenes.
- NeRF for better view-dependent effect & light transport.
- INR with mid/high level tasks.



(a) Capture Process



(b) Input



(c) Nerfie



(d) Nerfie Depth



# Thank you!

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