

NeRFactor:

Neural Factorization of Shape and
Reflectance Under an Unknown Illumination

(Xiuming ZHANG et al. SIGGRAPH Asia, 2021)

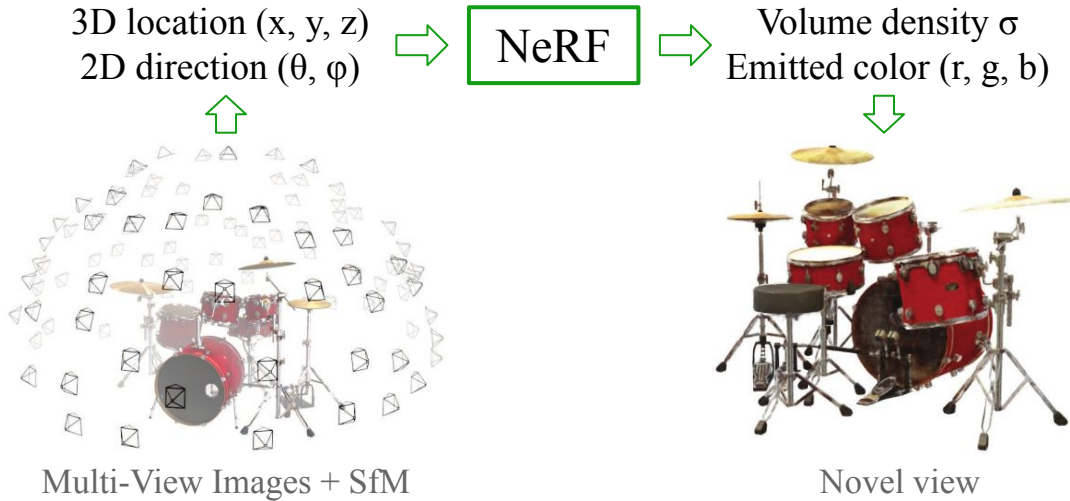
Lulin Zhang, 10/02/2023



NeRF (Neural Radiance Fields):

Render novel views by optimizing a continuous volumetric function.

Represent a scene using a fully-connected **deep network**.



Novel view rendering



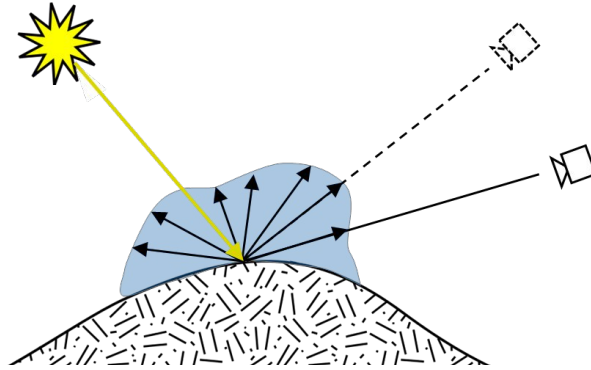
Unable to relight the scene

Outgoing light = ~~incoming light~~ + reflectance

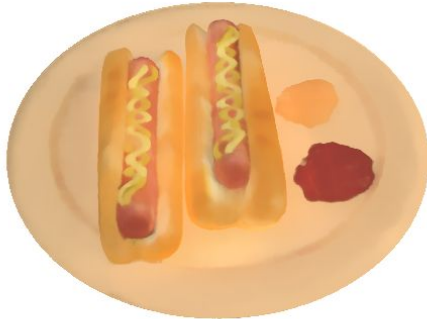
NeRFactor extends NeRF for relighting by modeling:

- Incoming **light**
- Surface **normal**
- **Reflectance**

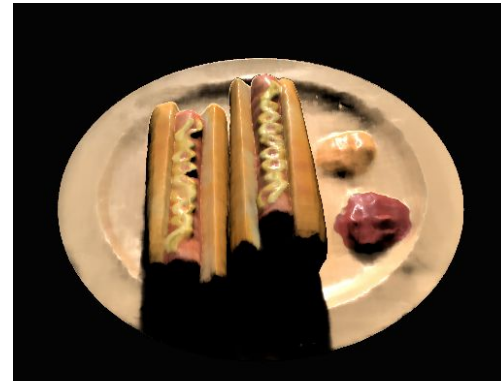
Reflectance:



BRDF: Bi-directional Reflectance Distribution Function


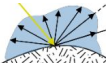













Albedo (Diffuse component)



Specular spatially-varying **BRDF**
(related to materials)

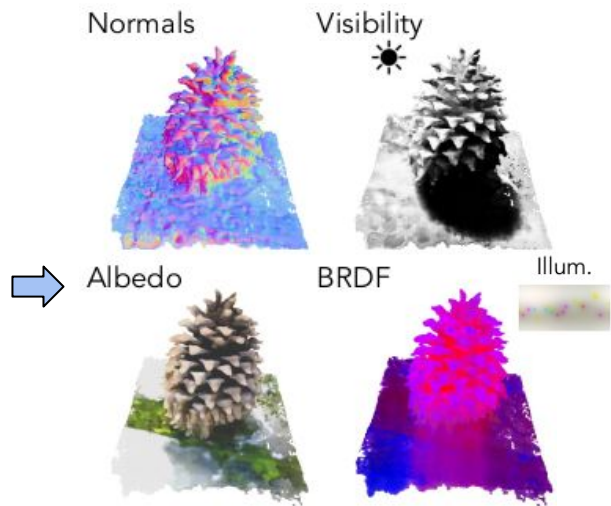
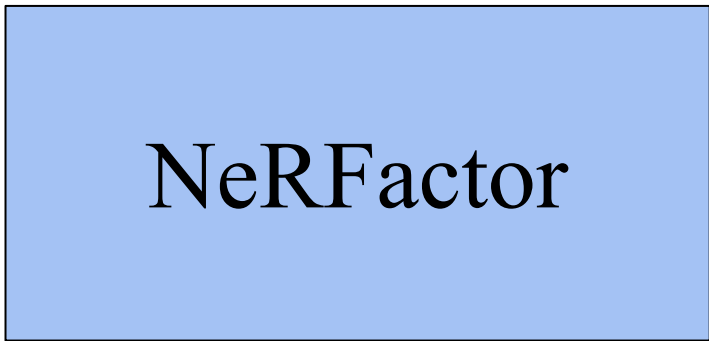
Recovering an object's geometry and material properties from captured images:

	Previous work	NeRFactor
 Illumination	Multiple known illumination	One unknown illumination
 BRDF	Analytic BRDF (e.g. microfacet models)	Data-driven BRDF
Only images as input	 (e.g. scanned geometry)	
 Spatially-varying reflectance		
 Model visibility or shadows		
 Represent object with multiple materials		



3D location (x, y, z)
2D direction (θ, ϕ)

Input



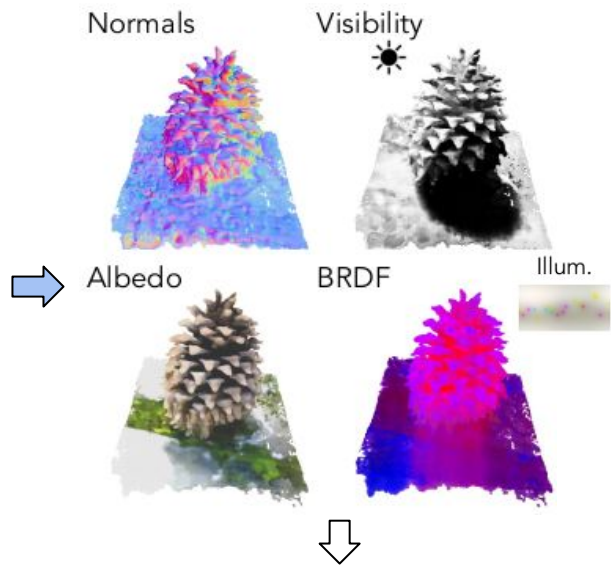
Output



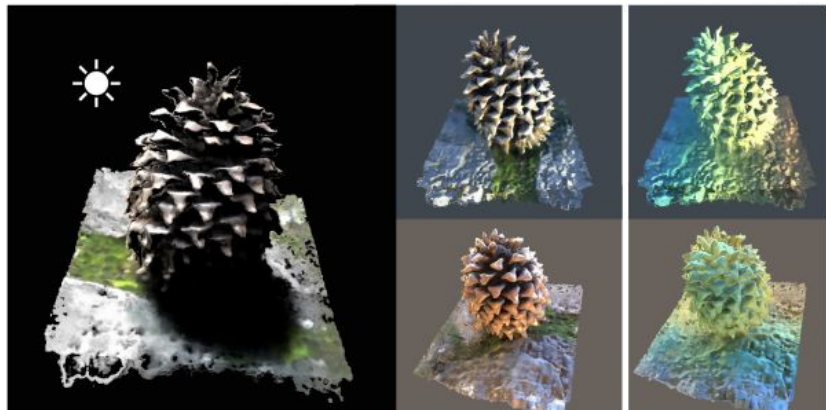
3D location (x, y, z)
2D direction (θ, ϕ)



NeRFactor



Applications:

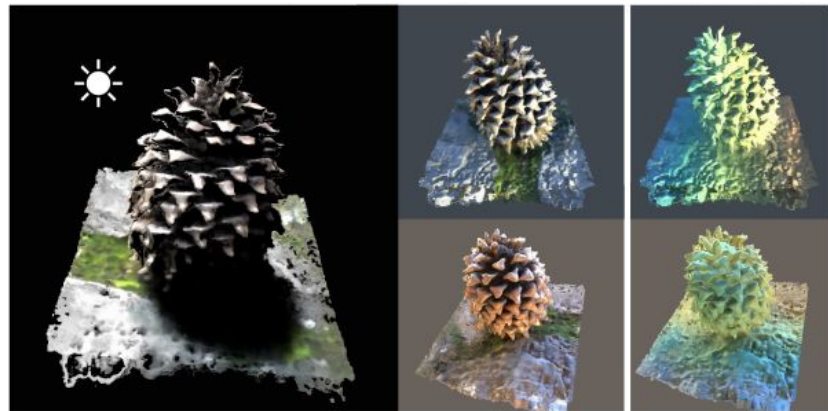
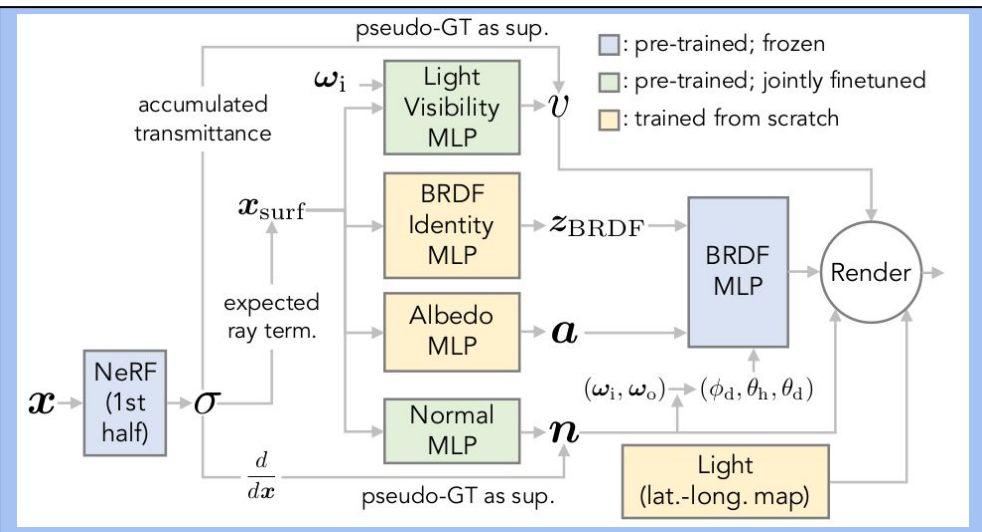
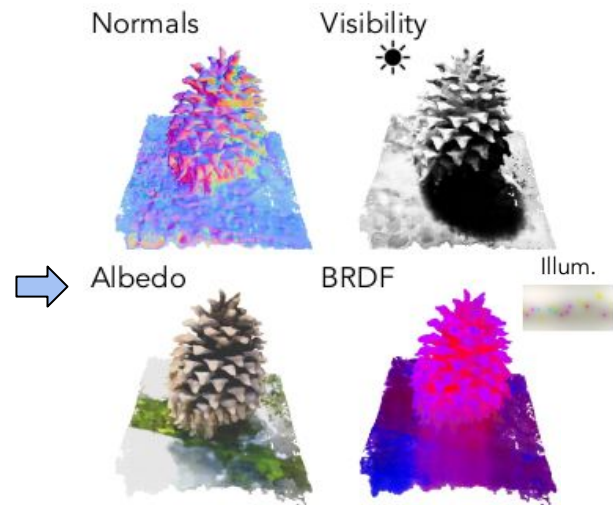


(1) Novel view rendering (2) Relighting (3) Material Editing



3D location (x, y, z)
2D direction (θ, ϕ)

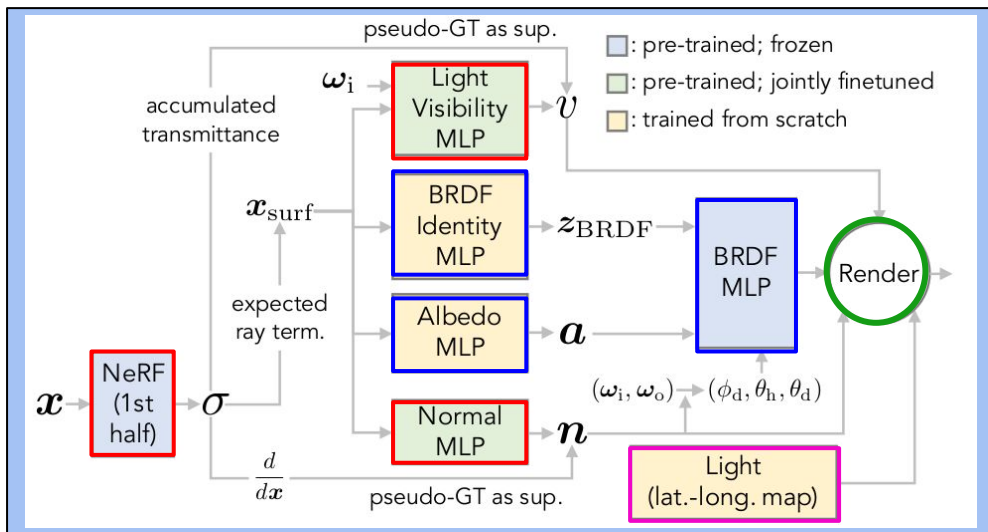
NeRFactor



(1) Novel view rendering (2) Relighting (3) Material Editing

NeRFactor includes 4 blocks:

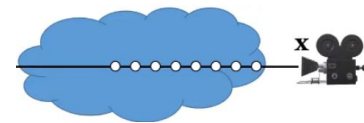
- **Shape**
- **Reflectance**
- **Light**
- **Render**



NeRFactor includes 4 blocks:

- **Shape**

Train **vanilla NeRF**

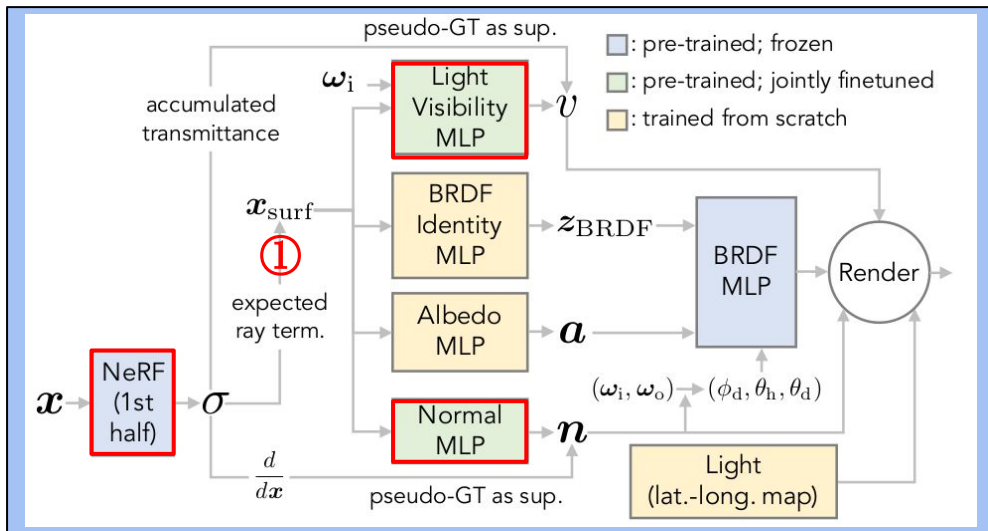


① **Surface location:**

March through NeRF's σ -volume to camera

*Surface is more efficient than volume

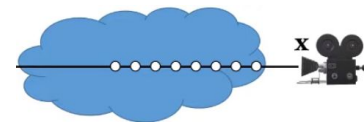
*as input later



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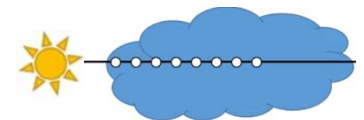
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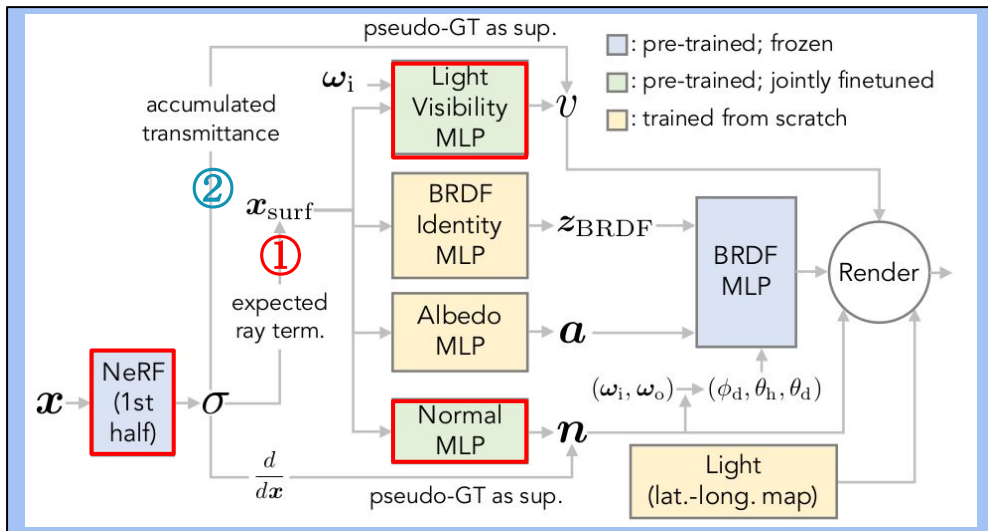
March through NeRF's σ -volume to camera



② **Light visibility:**

March through NeRF's σ -volume to each light location

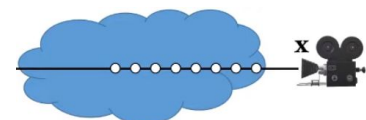
*as pseudo GT



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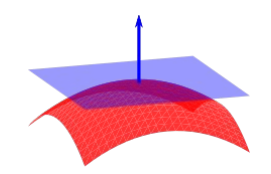
① **Surface location:**

March through NeRF's σ -volume to camera



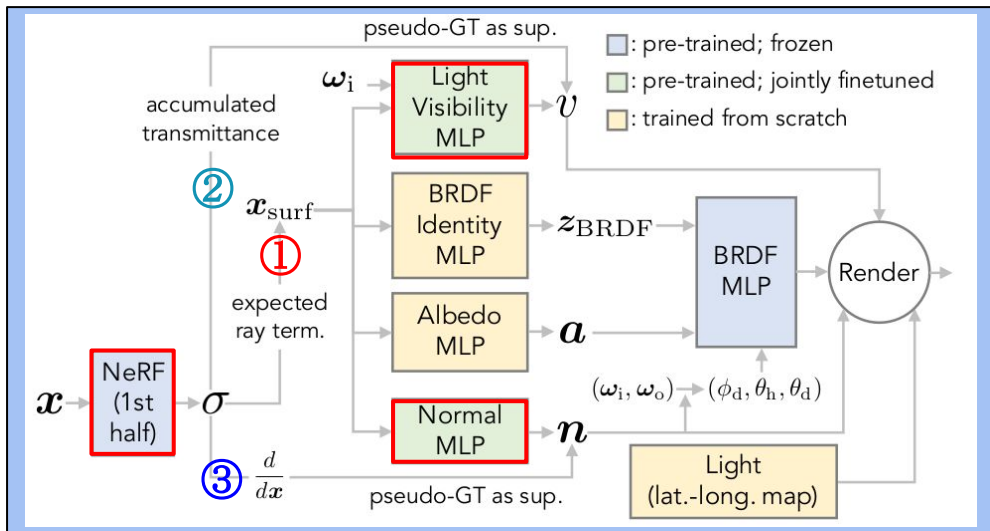
② **Light visibility:**

March through NeRF's σ -volume to each light location



③ **Normal:**

Calculate negative normalized gradient of NeRF's σ -volume
 *as pseudo GT



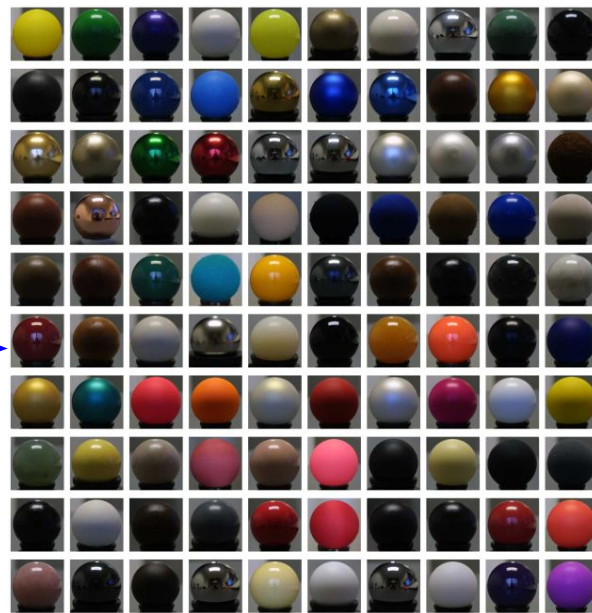
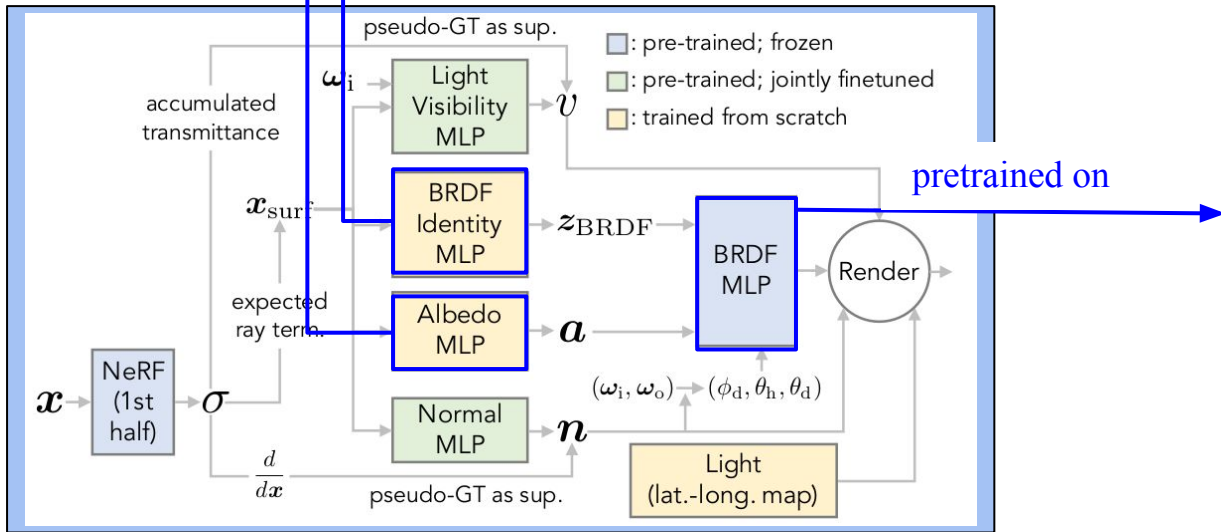
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- **Reflectance**

Data-driven BRDF + Albedo

*Albedo: diffuse component of reflectance
*Model visibility: separating shadows from albedo

Latent code: vector in an abstract M-D space

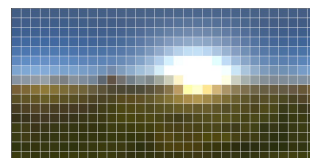


MERL dataset (real measured BRDFs)

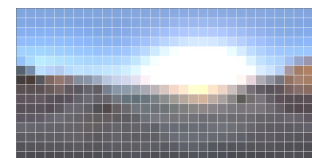
NeRFactor includes 4 blocks:

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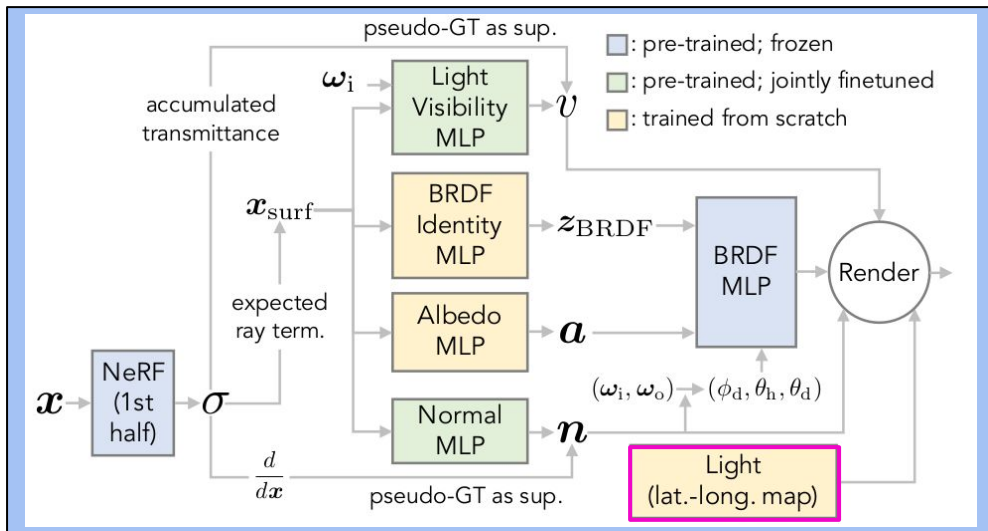
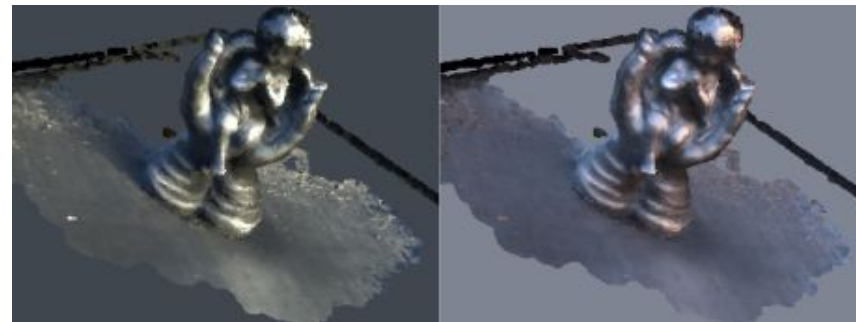
Estimate an HDR **light probe image** with size of 16*32



Sunrise



Sunset

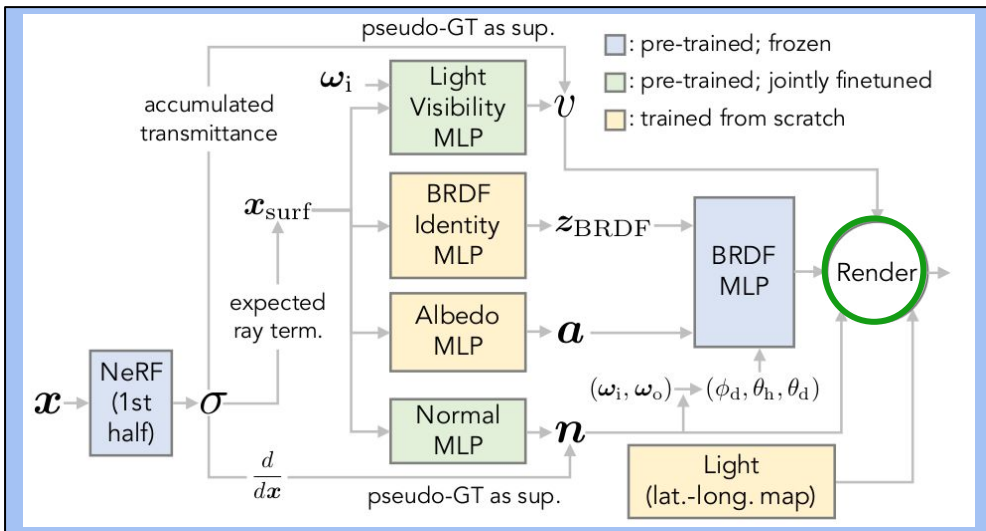


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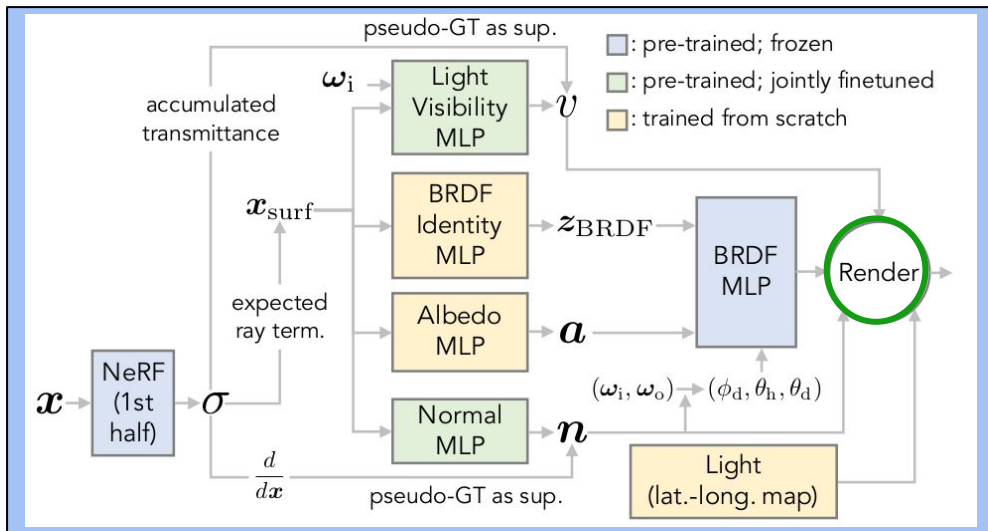
$$L_o(X, \hat{\omega}_o) = \int_{\mathbf{S}^2} L_i(X, \hat{\omega}_i) f_X(\hat{\omega}_i, \hat{\omega}_o) |\hat{\omega}_i \cdot \hat{n}| d\hat{\omega}_i$$

Outgoing light
Incoming light
Reflectance
Normal



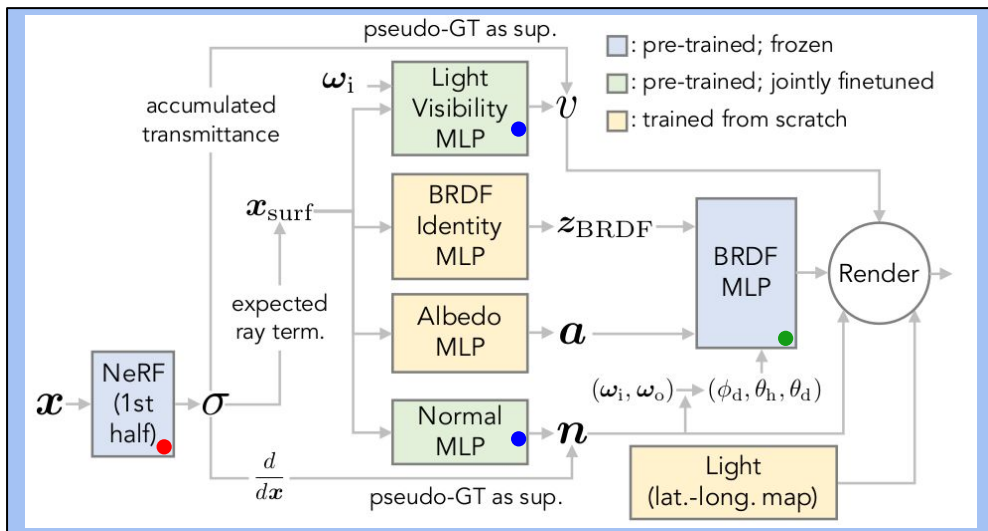
Supervisions:

- (1) **Rendering GT:** pixel RGB values
- (2) **BRDF GT:** real measured BRDFs in MERL
- (3) **pseudo GT:** calculated from shape estimation
- (4) **Smooth term:** smoothness is encouraged across spatial locations



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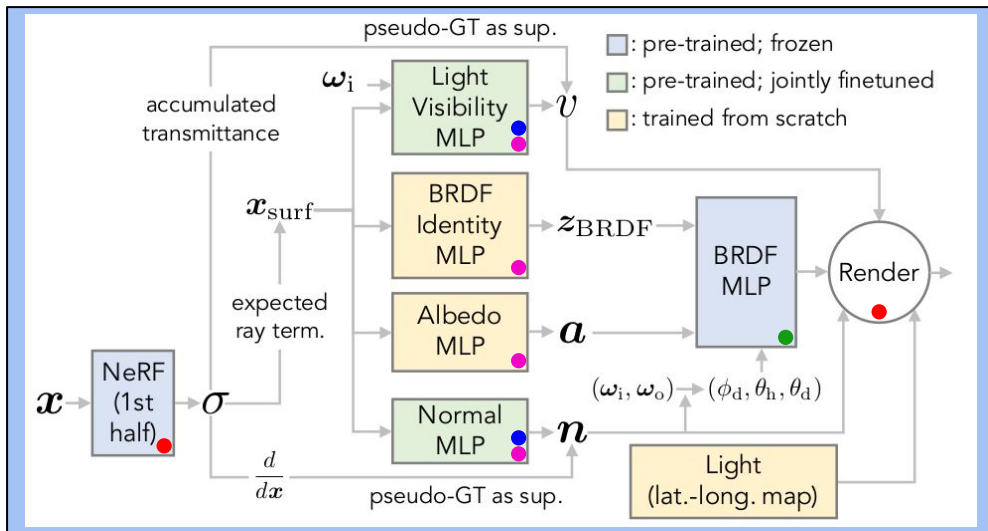
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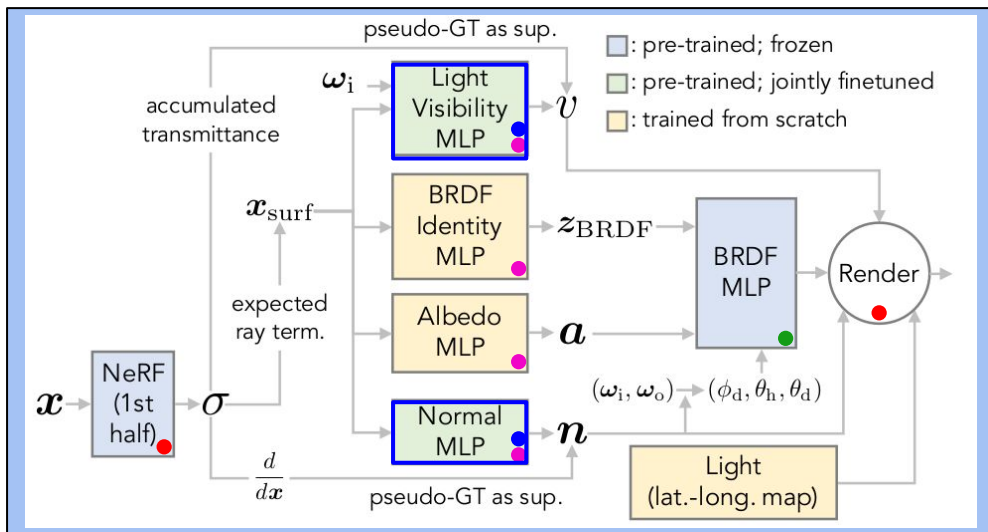


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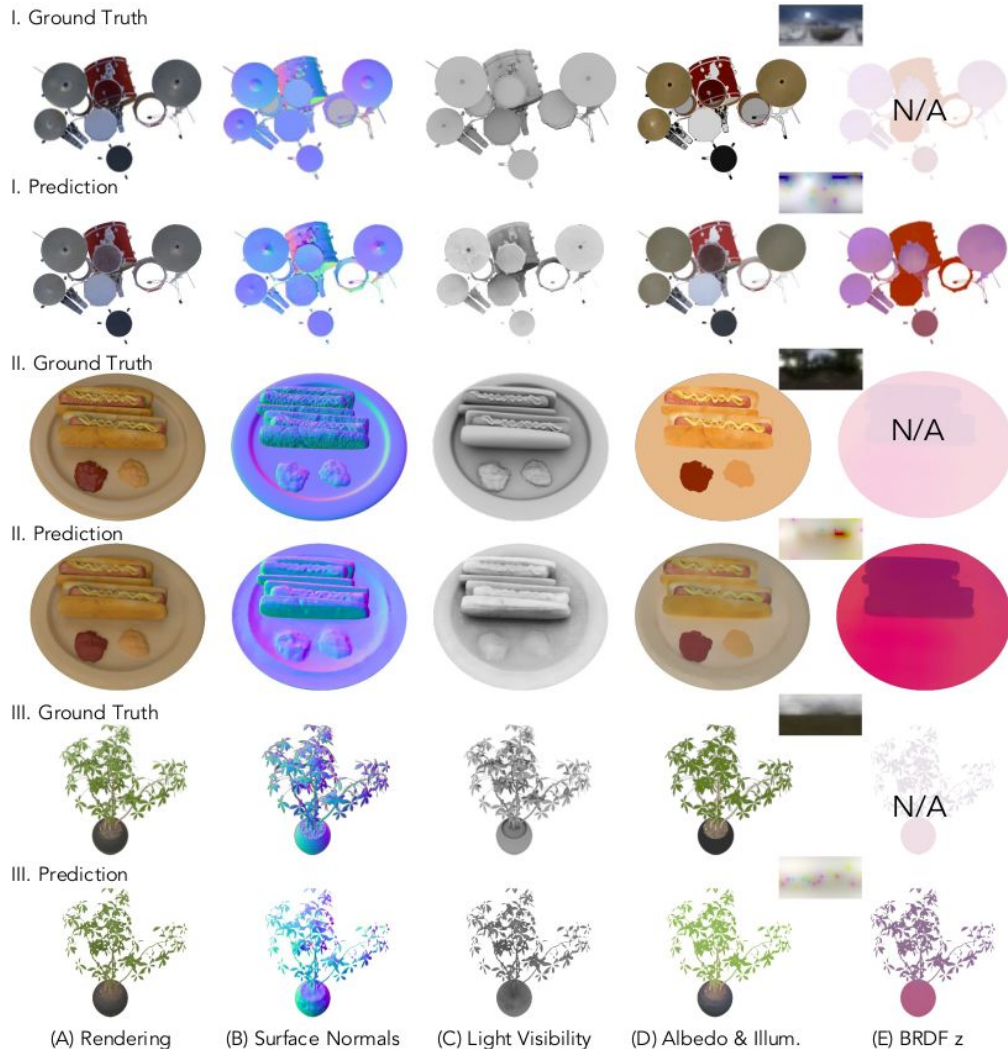


(1) Pre-train some MLPs with (1) (2) (3)

(2) Jointly train some MLPs with (1) (4)

Why pre-train first and jointly train later ?

To prevent the albedo or BRDF MLP from mistakenly attempting to explain away shadows.



Comparisons in point light relighting:



(A) Philip et al.
[2019]

(B) NeRFactor
(ours)

(C) Ground Truth

*poor geometry reconstruction is revealed in harsh lighting conditions.

(B) (C): NeRFactor predicts high-quality and smooth results.

(D): Albedo is recovered cleanly without shadow.

The predicted light probes correctly reflect the locations of the primary light sources.

(E) The predicted BRDFs correctly reflect different materials.

Thank you !