Recreating NeRF

This is a PyTorch implementation based on the paper: https://arxiv.org/abs/2003.08934. The code takes mostly after the officially tiny nerf implementation: https://colab.research.google.com/github/bmild/nerf/blob/master/tiny_nerf.ipynb

In [ ]:
```
!pip install numpy tqdm ipywidgets matplotlib
!pip3 install torch torchvision torchaudio
!pip install imageio
!pip install python-ffmpeg
!pip install imageio-ffmpeg
```

Imports + Data

In [1]:
```
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
import torch.nn.init as init
import time
import numpy as np
import torch.nn.functional as F
import os
from tqdm import tqdm
from ipywidgets import interactive, widgets

#Example data http://cseweb.ucsd.edu/~viscomp/projects/LF/papers/ECCV20/nerf/tiny_nerf_data.npz
```

Encoding + Model

$$\gamma(p) = (\sin(2^0\pi p), \cos(2^0\pi p), \ldots, \sin(2^{L-1}\pi p), \cos(2^{L-1}\pi p))$$

In [14]:
```
def encoding(x, L=10):
    rets = [x]
    for i in range(L):
        for fn in [torch.sin, torch.cos]:  # Use torch functions
            rets.append(fn(2. ** i * x))
    return torch.cat(rets, dim=-1)  # Concatenate along the last dimension

class NeRF(nn.Module):

  def __init__(self, pos_enc_dim = 63, view_enc_dim = 27, hidden = 256) -> None:
     super().__init__()

     self.linear1 = nn.Sequential(nn.Linear(pos_enc_dim,hidden),nn.ReLU())

     self.pre_skip_linear = nn.Sequential()
     for _ in range(4):
      self.pre_skip_linear.append(nn.Linear(hidden,hidden))
      self.pre_skip_linear.append(nn.ReLU())


     self.linear_skip = nn.Sequential(nn.Linear(hidden+pos_enc_dim,hidden),nn.ReLU())

     self.post_skip_linear = nn.Sequential()
     for _ in range(2):
      self.post_skip_linear.append(nn.Linear(hidden,hidden))
      self.post_skip_linear.append(nn.ReLU())

     self.density_layer = nn.Sequential(nn.Linear(hidden,1), nn.ReLU())

     self.linear2 = nn.Linear(hidden,hidden)

     self.color_linear1 = nn.Sequential(nn.Linear(hidden+view_enc_dim,hidden//2),nn.ReLU())
     self.color_linear2 = nn.Sequential(nn.Linear(hidden//2, 3),nn.Sigmoid())

     self.relu = nn.ReLU()
     self.sigmoid = nn.Sigmoid()


  def forward(self,input):

    # Extract pos and view dirs
    positions = input[..., :3]
    view_dirs = input[...,3:]

    # Encode
    pos_enc = encoding(positions,L=10)
    view_enc = encoding(view_dirs, L=4)

    x = self.linear1(pos_enc)
    x = self.pre_skip_linear(x)

    # Skip connection
    x = torch.cat([x, pos_enc], dim=-1)
    x = self.linear_skip(x)
```

```python
    x = self.post_skip_linear(x)

    # Density prediction
    sigma = self.density_layer(x)

    x = self.linear2(x)

    # Incoroporate view encoding
    x = torch.cat([x, view_enc],dim=-1)
    x = self.color_linear1(x)

    # Color Prediction
    rgb = self.color_linear2(x)

    return torch.cat([sigma, rgb], dim=-1)
```

Get Ray + Render

In [15]:

```python
def get_rays(H, W, focal, c2w):
    """
    Generate rays for a given camera configuration.

    Args:
      H: Image height.
      W: Image width.
      focal: Focal length.
      c2w: Camera-to-world transformation matrix (4x4).

    Returns:
      rays_o: Ray origins (H*W, 3).
      rays_d: Ray directions (H*W, 3).
    """
    device = c2w.device  # Get the device of c2w

    # Convert focal to float32 before moving to device
    if isinstance(focal, np.ndarray):
        focal = torch.tensor(focal.item(), dtype=torch.float32, device=device)
    elif not isinstance(focal, torch.Tensor):
        focal = torch.tensor(focal, dtype=torch.float32, device=device)
    elif focal.device != device:
        focal = focal.to(device)

    i, j = torch.meshgrid(
        torch.arange(W, dtype=torch.float32, device=device),
        torch.arange(H, dtype=torch.float32, device=device),
        indexing='xy'
    )

    # Process in chunks if needed for extremely high resolutions
    dirs = torch.stack(
        [(i - W * 0.5) / focal, -(j - H * 0.5) / focal, -torch.ones_like(i, device=device)], -1
    )

    # Matrix multiply in smaller batches if needed
    rays_d = torch.sum(dirs[..., None, :] * c2w[:3, :3], -1)
    rays_d = rays_d.reshape(-1, 3)
    rays_o = c2w[:3, -1].expand(rays_d.shape)

    return rays_o, rays_d

def render_rays(network_fn, rays_o, rays_d, near, far, N_samples, device, rand=False, embed_fn=None, chunk=512):
    def batchify(fn, chunk):
        return lambda inputs: torch.cat([fn(inputs[i:i+chunk]) for i in range(0, inputs.shape[0], chunk)], 0)

    # Sampling
    z_vals = torch.linspace(near, far, steps=N_samples, device=device)

    if rand:
        # Only add noise to each z_val when rand is True
        noise = torch.rand(z_vals.shape[:-1] + (N_samples,), device=device) * (far - near) / N_samples
        z_vals = z_vals + noise

    # More efficient way to create points
    rays_o_shaped = rays_o.unsqueeze(1)  # [batch, 1, 3]
    rays_d_shaped = rays_d.unsqueeze(1)  # [batch, 1, 3]
    z_vals_shaped = z_vals.unsqueeze(-1)  # [batch, N_samples, 1]

    # More memory-efficient ray point generation
    pts = rays_o_shaped + rays_d_shaped * z_vals_shaped  # [batch, N_samples, 3]

    # Normalize view directions and expand more efficiently
    rays_d_norm = torch.nn.functional.normalize(rays_d, dim=-1)
    view_dirs = rays_d_norm.unsqueeze(1).expand_as(pts)  # [batch, N_samples, 3]

    # Combine for network input
    input_pts = torch.cat((pts, view_dirs), dim=-1)  # [batch, N_samples, 6]

    # Clear intermediate tensors to free memory
    del pts, view_dirs, rays_o_shaped, rays_d_shaped, z_vals_shaped

    # Use smaller chunk size for network evaluation
```

```
    raw = batchify(network_fn, chunk)(input_pts)

    # Release input_pts memory
    del input_pts

    # The rest of the function remains similar
    sigma_a = raw[...,0]  # Shape: [batch, N_samples]
    rgb = raw[...,1:]    # Shape: [batch, N_samples, 3]

    # Improved volume rendering - compute dists more efficiently
    dists = torch.cat([
        z_vals[..., 1:] - z_vals[..., :-1],
        torch.ones_like(z_vals[..., :1]) * 1e10
    ], dim=-1)

    alpha = 1. - torch.exp(-sigma_a * dists)
    alpha = alpha.unsqueeze(-1)  # [batch, N_samples, 1]

    # Computing transmittance with a more memory-efficient approach
    ones_shape = list(alpha.shape)
    ones_shape[1] = 1
    ones = torch.ones(ones_shape, device=device)

    # Compute transmittance efficiently
    T = torch.cumprod(
        torch.cat([ones, 1. - alpha + 1e-10], dim=1),
        dim=1
    )[:, :-1]  # [batch, N_samples, 1]

    weights = alpha * T

    # Compute final colors and depths
    rgb_map = torch.sum(weights * rgb, dim=1)
    depth_map = torch.sum(weights.squeeze(-1) * z_vals, dim=-1)
    acc_map = torch.sum(weights.squeeze(-1), dim=-1)

    return rgb_map, depth_map, acc_map
```

Train Loop

In [16]:
```
def train(images, poses, H, W, focal, testpose, testimg, device):
    print(f"Using device: {device}")
    model = NeRF().to(device)

    criterion = nn.MSELoss(reduction='mean')
    optimizer = torch.optim.Adam(model.parameters(), lr=5e-4)
    scheduler = torch.optim.lr_scheduler.ExponentialLR(optimizer, gamma=0.99)

    n_iter = 1000
    n_samples = 64
    i_plot = 50
    psnrs = []
    iternums = []
    t = time.time()

    # Reduce batch size or use smaller image dimensions for training
    ray_batch_size = 1024  # Smaller batch size for rays
    downscale_factor = 2   # Downscale images for training

    # Downscale dimensions for training
    h_train = H // downscale_factor
    w_train = W // downscale_factor

    # Convert data to tensors ONCE but keep on CPU
    images_tensor = torch.from_numpy(images).float()
    poses_tensor = torch.from_numpy(poses).float()

    for i in range(n_iter):
        # Select a random image for training
        img_i = np.random.randint(images.shape[0])

        # Get target image and pose
        target = images_tensor[img_i]  # Keep on CPU initially
        pose = poses_tensor[img_i].to(device)  # Move to device only when needed

        # Downscale for training
        if downscale_factor > 1:
            target_resized = F.interpolate(target.permute(2, 0, 1).unsqueeze(0),
                                          size=(h_train, w_train),
                                          mode='bilinear').squeeze(0).permute(1, 2, 0)
        else:
            target_resized = target

        # Get rays for the downscaled image
        rays_o, rays_d = get_rays(h_train, w_train, focal / downscale_factor, pose)

        # Use only a subset of rays for training (random sampling)
        select_inds = np.random.choice(rays_o.shape[0], size=ray_batch_size, replace=False)
        rays_o = rays_o[select_inds].to(device)
        rays_d = rays_d[select_inds].to(device)
        target_s = target_resized.reshape(-1, 3)[select_inds].to(device)
```

```
        optimizer.zero_grad()

        # Use smaller chunk size for processing
        chunk_size = 512  # Smaller chunk size reduces memory usage
        rgb, depth, acc = render_rays(model, rays_o, rays_d, near=2., far=6.,
                                     N_samples=n_samples, device=device,
                                     rand=True, chunk=chunk_size)

        # Compute loss on the ray batch
        loss = criterion(rgb, target_s)

        loss.backward()
        optimizer.step()

        # Clean up to free memory
        del rays_o, rays_d, rgb, depth, acc, target_s
        torch.cuda.empty_cache() if torch.cuda.is_available() else None

        if i % i_plot == 0:
            print(f'Iteration: {i}, Loss: {loss.item():.6f}, Time: {(time.time() - t) / i_plot:.2f} secs per iter')
            t = time.time()

            # Evaluate on a subset of the test image to save memory
            test_ray_batch_size = 4096  # Larger batch for test, but still limited
            # In the training loop where we evaluate the test image:
            with torch.no_grad():
                # Make sure testpose is on the correct device
                testpose_device = testpose.to(device)

                # Get full resolution rays for test image
                test_rays_o, test_rays_d = get_rays(H, W, focal, testpose_device)

                # Process test rays in smaller batches
                test_rgb_parts = []
                for j in range(0, test_rays_o.shape[0], test_ray_batch_size):
                    end_idx = min(j + test_ray_batch_size, test_rays_o.shape[0])
                    batch_o = test_rays_o[j:end_idx]
                    batch_d = test_rays_d[j:end_idx]

                    rgb_batch, _, _ = render_rays(model, batch_o, batch_d, near=2., far=6.,
                                                 N_samples=n_samples, device=device, chunk=chunk_size)

                    # Move results to CPU immediately
                    test_rgb_parts.append(rgb_batch.cpu())

                    # Clean up batch
                    del batch_o, batch_d, rgb_batch
                    if torch.cuda.is_available():
                        torch.cuda.empty_cache()

                # Combine batches on CPU
                test_rgb = torch.cat(test_rgb_parts, dim=0)
                test_rgb = test_rgb.reshape(H, W, 3)

                # Make sure testimg is on CPU for comparison
                testimg_cpu = testimg.cpu()

                # Compute PSNR on CPU to save memory
                test_loss = F.mse_loss(test_rgb, testimg_cpu)
                psnr = -10. * torch.log10(test_loss)

                psnrs.append(psnr.item())
                iternums.append(i)

                # Plot
                plt.figure(figsize=(10,4))
                plt.subplot(121)
                plt.imshow(test_rgb.numpy())
                plt.title(f'Iteration: {i}')
                plt.subplot(122)
                plt.plot(iternums, psnrs)
                plt.title('PSNR')
                plt.show()

                # Clean up
                del test_rgb, test_rgb_parts, test_loss

        # Step learning rate scheduler
        if (i + 1) % 100 == 0:
            scheduler.step()

    return model
```

Load Data

In [17]:

```
# Load data
data = np.load('nerf_dataset/nerf_dataset.npz')
images = data['images'].astype(np.float32)
poses = data['poses'].astype(np.float32)
focal = data['focal'].astype(np.float32)  # Convert focal to float32
H, W = images.shape[1:3]
print(images.shape, poses.shape, focal)
```

```python
# Check if MPS is available
device = "cuda" if torch.cuda.is_available() else "cpu"
if torch.backends.mps.is_available():
    device = "mps"

# Split into training and test sets
# Use the last image as test image
test_idx = -1  # Use the last image as the test image
testimg = images[test_idx]
testpose = poses[test_idx]

# Use all other images for training (excluding the test image)
if test_idx == -1:
    train_images = images[:-1]
    train_poses = poses[:-1]
else:
    # If using a specific index
    train_images = np.concatenate([images[:test_idx], images[test_idx+1:]], axis=0)
    train_poses = np.concatenate([poses[:test_idx], poses[test_idx+1:]], axis=0)

# Ensure images have 3 channels (RGB)
if train_images.shape[-1] > 3:
    print(f"Original image shape: {train_images.shape}, trimming to 3 channels")
    train_images = train_images[...,:3]
    testimg = testimg[...,:3]

# Display test image
plt.figure(figsize=(8, 8))
plt.imshow(testimg)
plt.title("Test Image")
plt.axis('off')
plt.show()

# Convert tensors to the selected device with float32 dtype
testimg = torch.from_numpy(testimg).float().to(device)
testpose = torch.from_numpy(testpose).float().to(device)

# Now use train_images and train_poses in your training loop
print(f"Training set: {train_images.shape} images")
print(f"Test image: {testimg.shape}")
```

```
(2, 1080, 878, 3) (2, 4, 4) 2501.6567
```

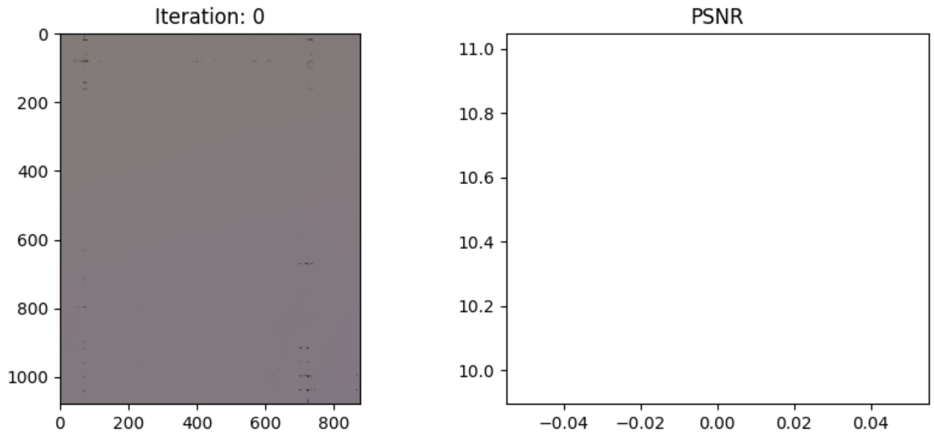
Test Image

```
Training set: (1, 1080, 878, 3) images
Test image: torch.Size([1080, 878, 3])
```

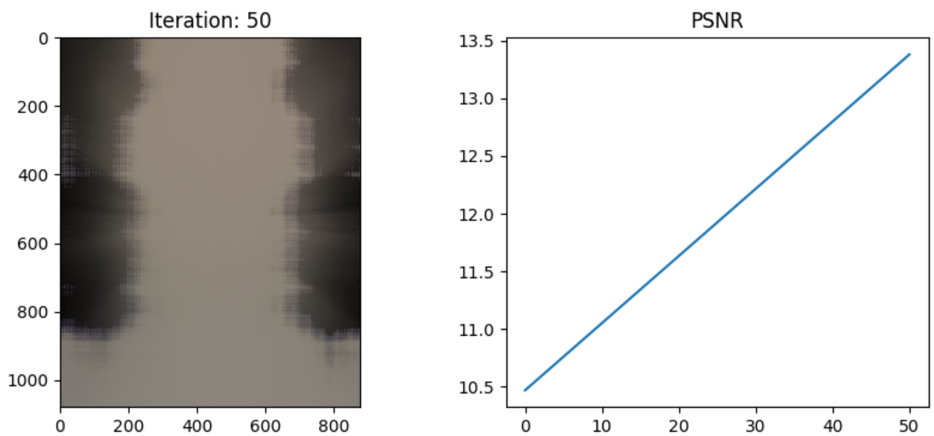
Train

In [18]:
```python
model = train(train_images, train_poses, H, W, focal, testpose, testimg, device)
```

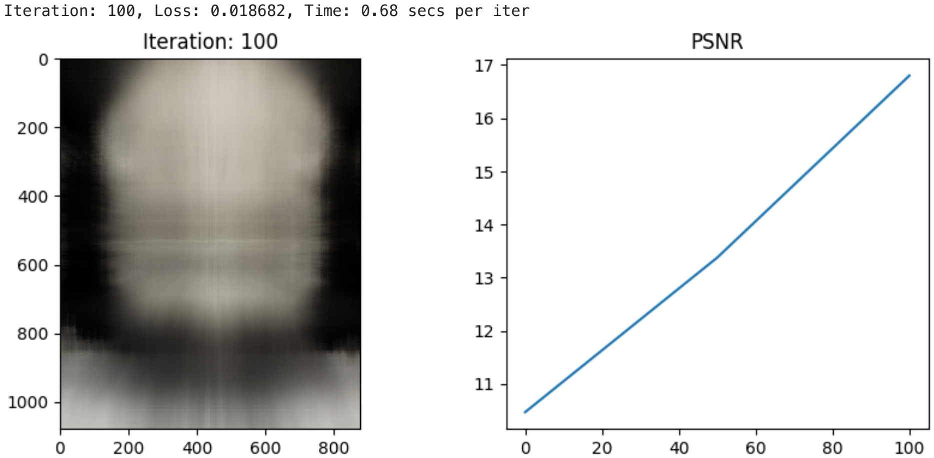
```
Using device: mps
Iteration: 0, Loss: 0.088453, Time: 0.01 secs per iter
```



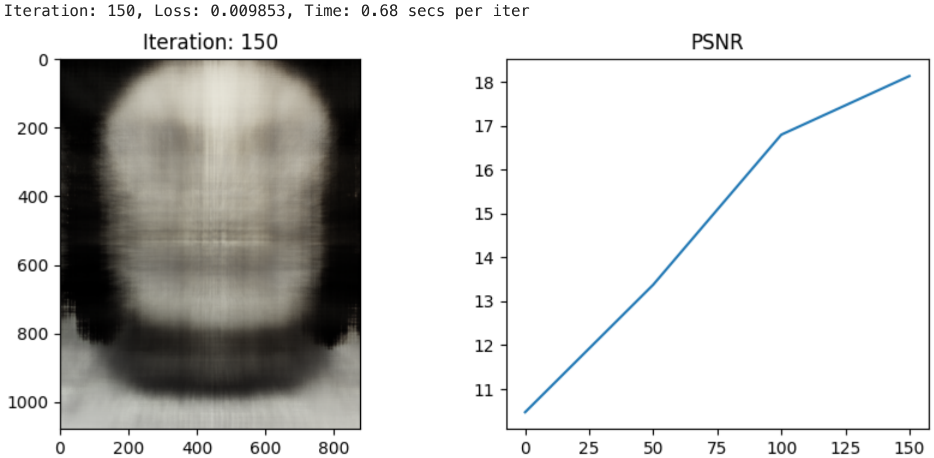

```
Iteration: 50, Loss: 0.044452, Time: 0.69 secs per iter
```



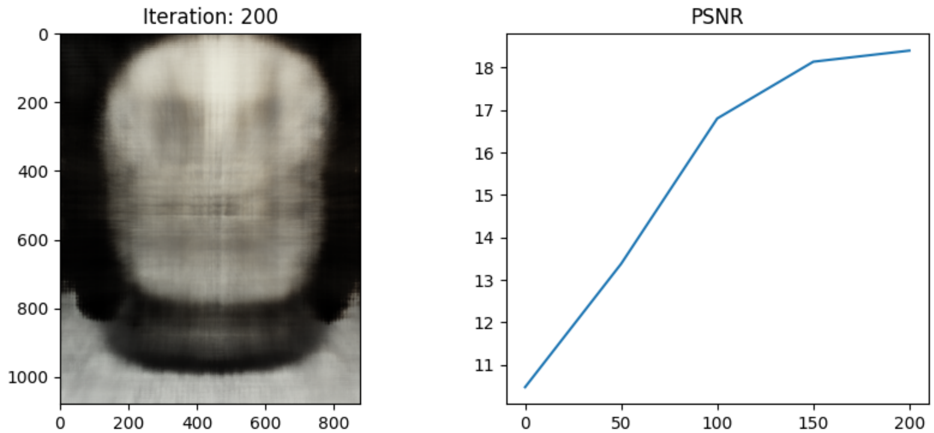

```
Iteration: 100, Loss: 0.018682, Time: 0.68 secs per iter
```



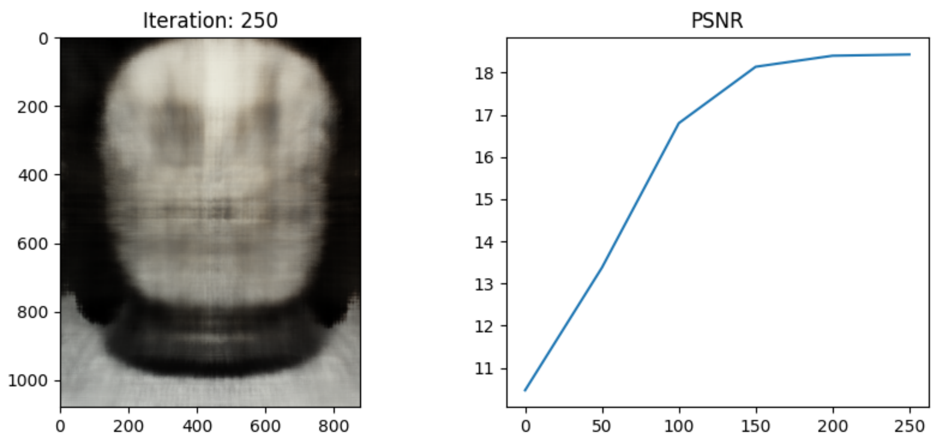

```
Iteration: 150, Loss: 0.009853, Time: 0.68 secs per iter
```



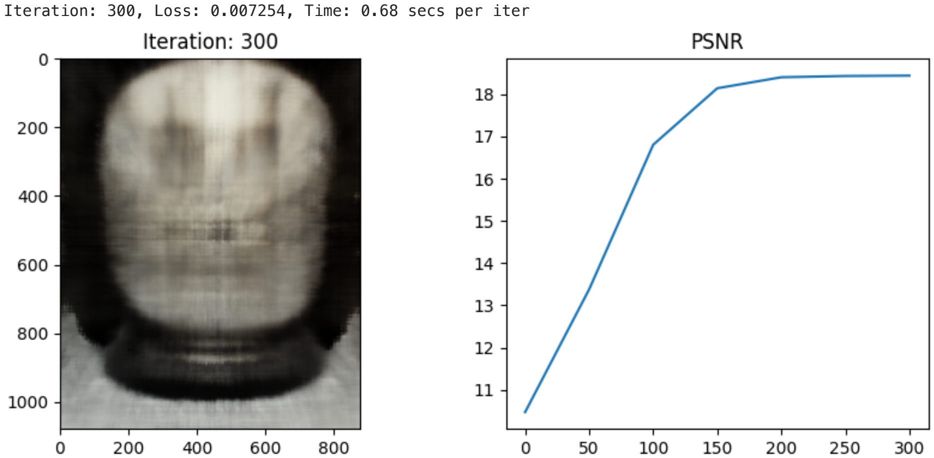

```
Iteration: 200, Loss: 0.008927, Time: 0.68 secs per iter
```



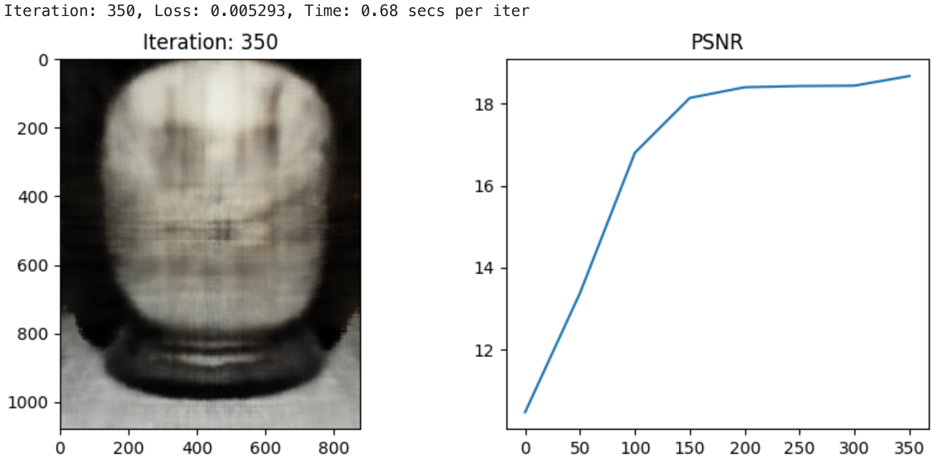
Iteration: 250, Loss: 0.009086, Time: 0.68 secs per iter



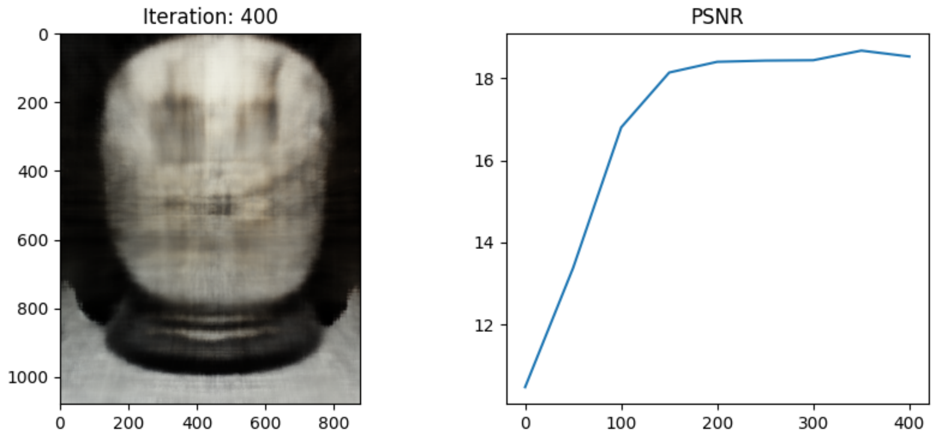
Iteration: 300, Loss: 0.007254, Time: 0.68 secs per iter



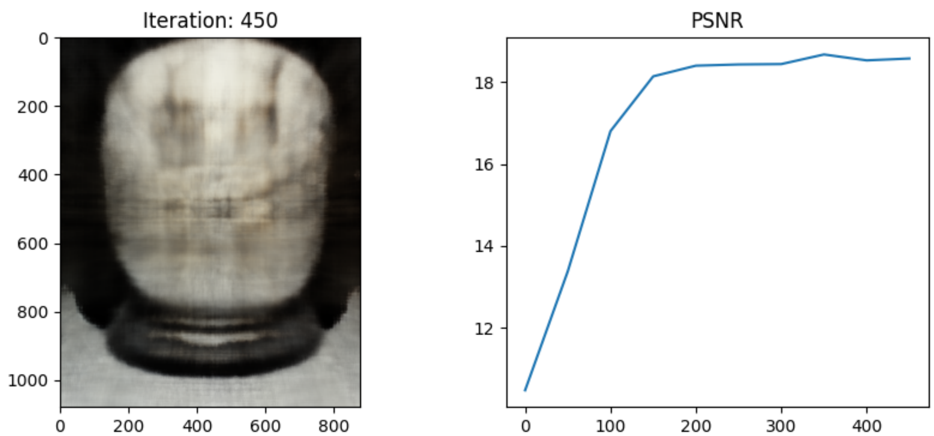
Iteration: 350, Loss: 0.005293, Time: 0.68 secs per iter



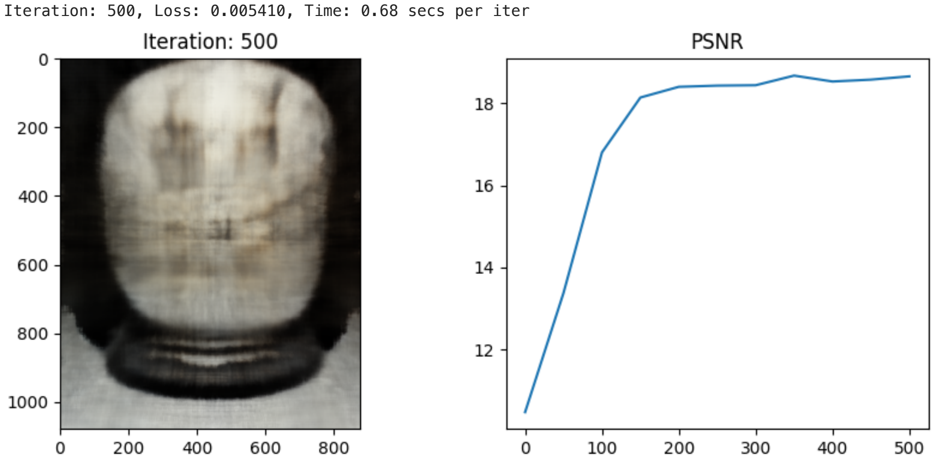
Iteration: 400, Loss: 0.005389, Time: 0.68 secs per iter



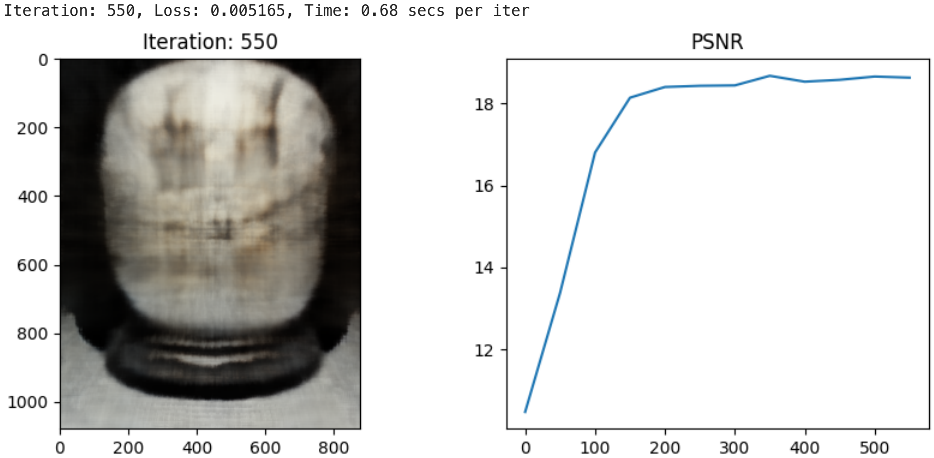
Iteration: 450, Loss: 0.006313, Time: 0.69 secs per iter



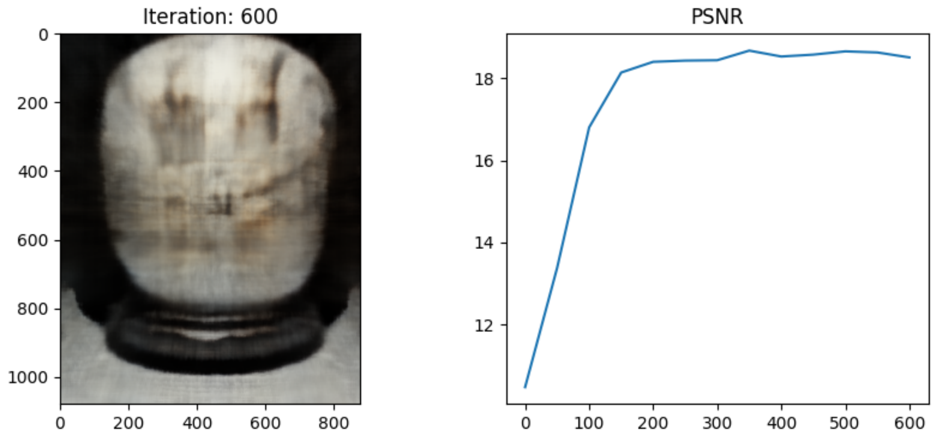
Iteration: 500, Loss: 0.005410, Time: 0.68 secs per iter



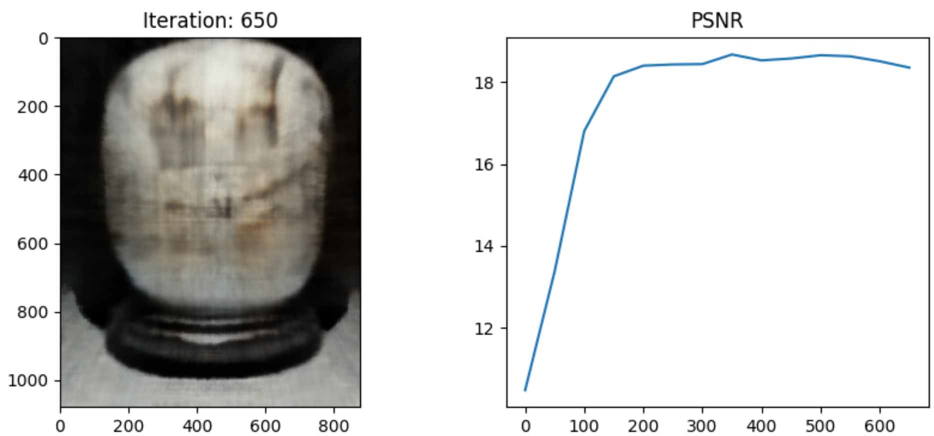
Iteration: 550, Loss: 0.005165, Time: 0.68 secs per iter



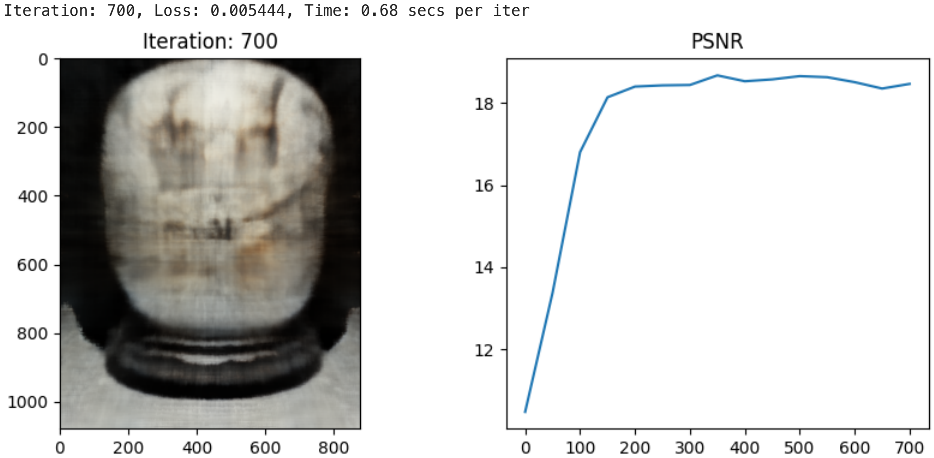
Iteration: 600, Loss: 0.005095, Time: 0.68 secs per iter



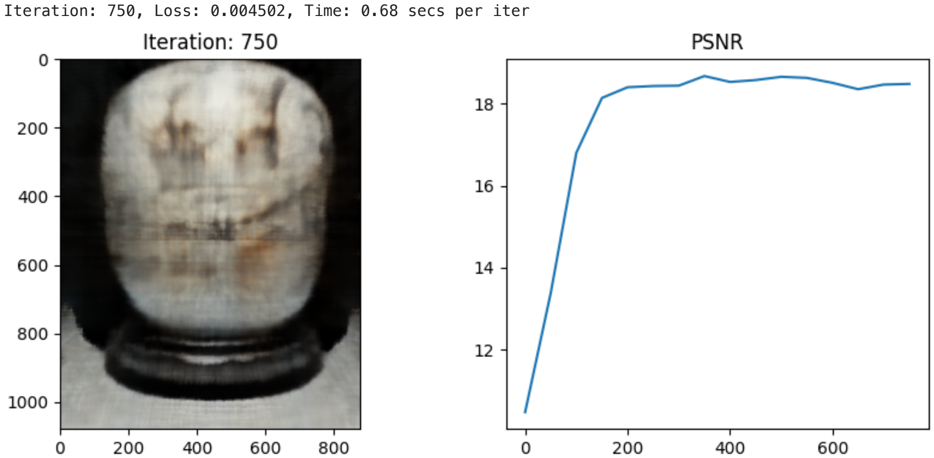
Iteration: 650, Loss: 0.005213, Time: 0.68 secs per iter



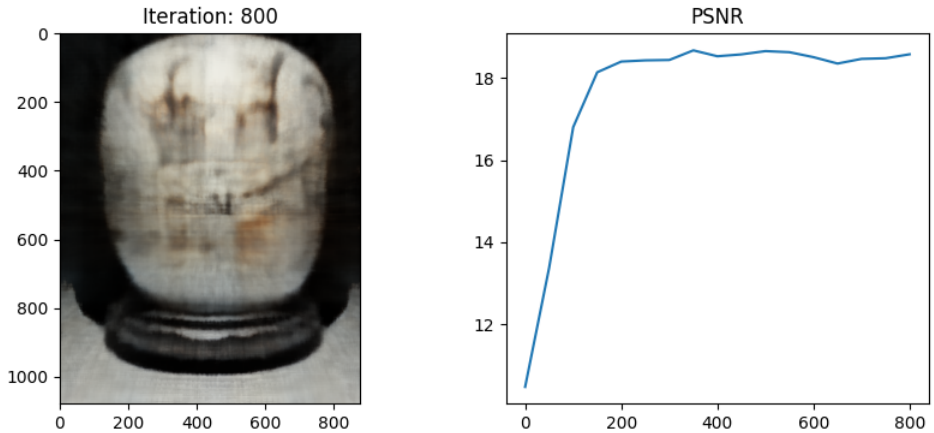
Iteration: 700, Loss: 0.005444, Time: 0.68 secs per iter



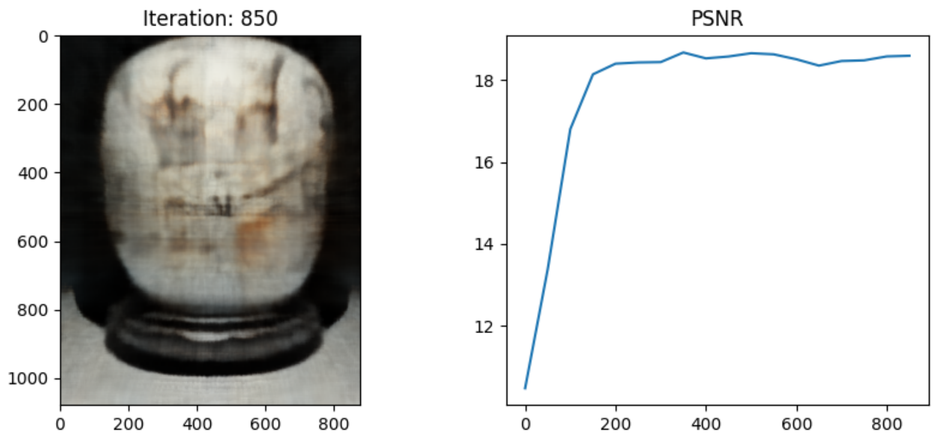
Iteration: 750, Loss: 0.004502, Time: 0.68 secs per iter



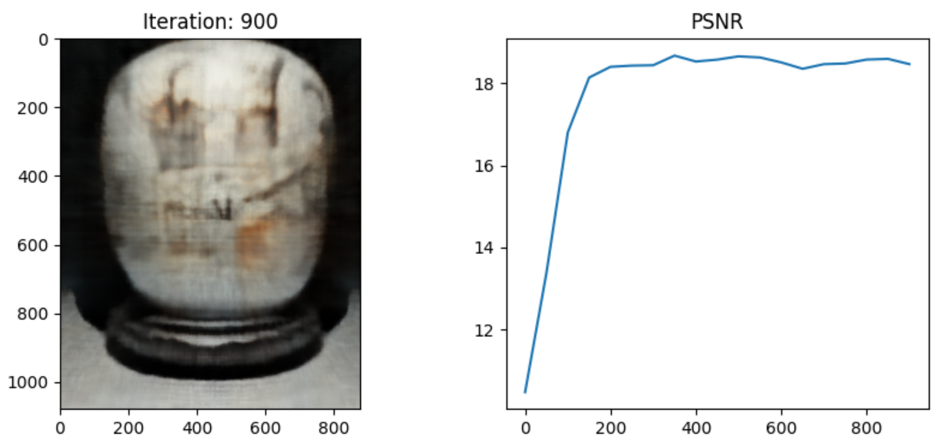
Iteration: 800, Loss: 0.003979, Time: 0.68 secs per iter



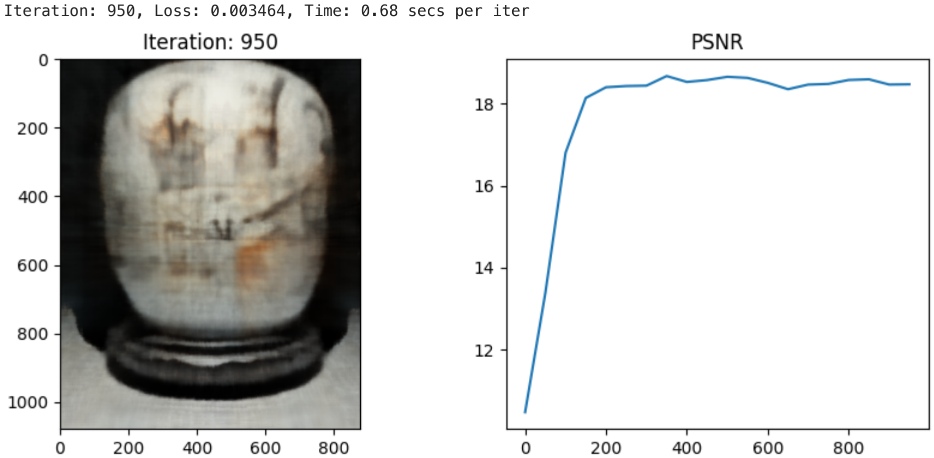

```
Iteration: 850, Loss: 0.004116, Time: 0.68 secs per iter
```




```
Iteration: 900, Loss: 0.002715, Time: 0.68 secs per iter
```




```
Iteration: 950, Loss: 0.003464, Time: 0.68 secs per iter
```



Render Video

In [27]:
```
# Transformation matrices in PyTorch
trans_t = lambda t: torch.tensor([
    [1, 0, 0, 0],
    [0, 1, 0, 0],
    [0, 0, 1, t],
    [0, 0, 0, 1]
], dtype=torch.float32, device=device)

rot_phi = lambda phi: torch.tensor([
    [1, 0, 0, 0],
    [0, torch.cos(phi), -torch.sin(phi), 0],
    [0, torch.sin(phi), torch.cos(phi), 0],
    [0, 0, 0, 1]
], dtype=torch.float32, device=device)

rot_theta = lambda th: torch.tensor([
    [torch.cos(th), 0, -torch.sin(th), 0],
    [0, 1, 0, 0],
    [torch.sin(th), 0, torch.cos(th), 0],
    [0, 0, 0, 1]
], dtype=torch.float32, device=device)

# Pose function with spherical coordinates
def pose_spherical(theta, phi, radius):
    c2w = trans_t(radius)
    c2w = torch.matmul(rot_phi(torch.tensor([phi / 180. * np.pi], dtype=torch.float32, device=device)), c2w)
    c2w = torch.matmul(rot_theta(torch.tensor([theta / 180. * np.pi], dtype=torch.float32, device=device)), c2w)
    c2w = torch.tensor([[-1, 0, 0, 0], [0, 0, 1, 0], [0, 1, 0, 0], [0, 0, 0, 1]],
                       dtype=torch.float32, device=device) @ c2w
    return c2w

# Function for rendering based on user input
def f(**kwargs):
    c2w = pose_spherical(**kwargs)
    rays_o, rays_d = get_rays(H, W, focal, c2w[:3, :4])  # Get rays (this is a placeholder)
    c2w, rays_o, rays_d = map(lambda t: t.to(device), (c2w, rays_o, rays_d))
    with torch.no_grad():
      rgb, depth, acc = render_rays(model, rays_o, rays_d, near=2., far=6., N_samples=64, device=device)  # Render rays
    rgb = rgb.reshape(H, W, 3).cpu().detach()
    img = torch.clamp(rgb, 0, 1).numpy()  # Clamp RGB values between 0 and 1 and convert to numpy

    plt.figure(2, figsize=(20, 6))
    plt.imshow(img)
    plt.show()

# Interactive slider setup for theta, phi, and radius
sldr = lambda v, mi, ma: widgets.FloatSlider(
    value=v,
    min=mi,
    max=ma,
    step=.01,
)

names = [
    ['theta', [100., 0., 360]],
    ['phi', [-30., -90, 0]],
    ['radius', [4., 3., 5.]],
]

interactive_plot = interactive(f, **{s[0]: sldr(*s[1]) for s in names})
output = interactive_plot.children[-1]
output.layout.height = '350px'
interactive_plot
```

Out[27]:
```
interactive(children=(FloatSlider(value=100.0, description='theta', max=360.0, step=0.01), FloatSlider(value=-…
```

In [24]:
```
frames = []
for th in tqdm(np.linspace(0., 360., 120, endpoint=False)):
    c2w = pose_spherical(th, -30., 4.)
    rays_o, rays_d = get_rays(H, W, focal, c2w[:3,:4])
    c2w, rays_o, rays_d = map(lambda t: t.to(device), (c2w, rays_o, rays_d))
    with torch.no_grad():
        rgb, depth, acc = render_rays(model, rays_o, rays_d, near=2., far=6., N_samples=64, device=device)
        rgb = rgb.reshape(H, W, 3)
        frames.append((255*np.clip(rgb.cpu().detach().numpy(),0,1)).astype(np.uint8))

import imageio
f = 'video.mp4'
imageio.mimwrite(f, frames, fps=30, quality=7)
```

```
  0%|          | 0/120 [00:00<?, ?it/s]
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
Cell In[24], line 7
      5 c2w, rays_o, rays_d = map(lambda t: t.to(device), (c2w, rays_o, rays_d))
      6 with torch.no_grad():
----> 7     rgb, depth, acc = render_rays(model, rays_o, rays_d, near=2., far=6., N_samples=64, device=device)
      8     rgb = rgb.reshape(H, W, 3)
      9     frames.append((255*np.clip(rgb.cpu().detach().numpy(),0,1)).astype(np.uint8))

Cell In[15], line 61, in render_rays(network_fn, rays_o, rays_d, near, far, N_samples, device, rand, embed_fn, chunk)
     58 z_vals_shaped = z_vals.unsqueeze(-1)  # [batch, N_samples, 1]
     60 # More memory-efficient ray point generation
---> 61 pts = rays_o_shaped + rays_d_shaped * z_vals_shaped  # [batch, N_samples, 3]
     63 # Normalize view directions and expand more efficiently
     64 rays_d_norm = torch.nn.functional.normalize(rays_d, dim=-1)

RuntimeError: MPS backend out of memory (MPS allocated: 18.08 GB, other allocations: 1.09 MB, max allowed: 18.13 GB). Tried to allocate 69
4.51 MB on private pool. Use PYTORCH_MPS_HIGH_WATERMARK_RATIO=0.0 to disable upper limit for memory allocations (may cause system failur
e).
```

In [ ]:

```
f = 'video.gif'
imageio.mimwrite(f, frames, fps=30)
```

In [ ]:

```
from IPython.display import HTML
from base64 import b64encode
mp4 = open('video.mp4','rb').read()
data_url = "data:video/mp4;base64," + b64encode(mp4).decode()
HTML("""
<video width=400 controls autoplay loop>
      <source src="%s" type="video/mp4">
</video>
""" % data_url)
```