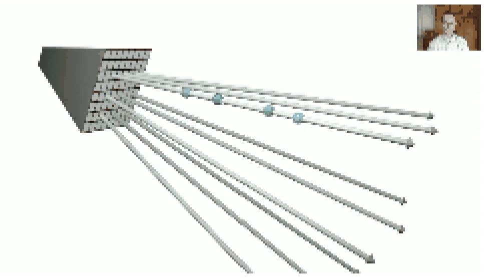
Nerf运行流程解析

上接：[体渲染]()

前置知识：[光线行进算法]()、[相机的内外参数]()

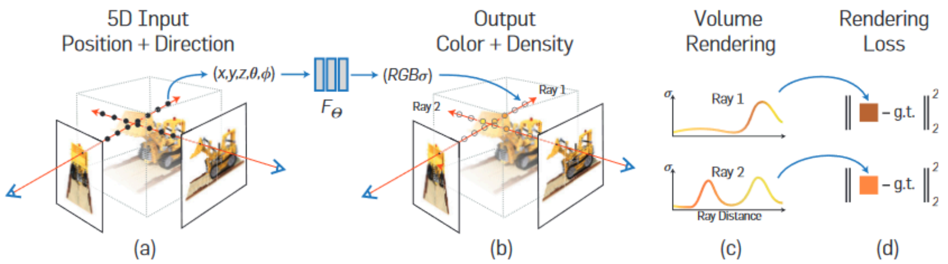
从论文中给出的系统结构图可知，Nerf中的DNN输入是相机位置(x,y,z)和射线朝向(θ,ϕ)，其组成5元组表示一条光路；DNN输出是这条光路的各离散采样区间δ_n内的粒子颜色c_n和其粒子密度σ_n（即光学厚度），之后，按照上述离散化体渲染公式进行积分操作，即得到这条光路射出的光线颜色，就像这样：



于是，渲染过程如下：

1. 指定相机的外参（位置、方向等）和内参（焦距、视野、分辨率等）根据外参内参计算出需要采样的各光路的(x,y,z,θ,ϕ)
2. 将每个光路的(x,y,z,θ,ϕ)输入DNN，计算得到光路上各离散采样区间δ_n内的颜色c_n和粒子密度σ_n
3. 按照离散化体渲染公式进行积分操作，即得到每条采样光路的颜色
4. 根据这些采样光路的颜色和相机内参，计算出相机拍到的图像
5. 上面这个离散化体渲染公式很显然是可微的，所以将计算得到的图像和Ground truth作差进行反向传播训练。

Figure 2. An overview of our neural radiance field scene representation and differentiable rendering procedure. We synthesize images by sampling 5D coordinates (location and viewing direction) along camera rays (a), feeding those locations into an MLP to produce a color and volume density (b), and using volume rendering techniques to composite these values into an image (c). This rendering function is differentiable, so we can optimize our scene representation by minimizing the residual between synthesized and ground truth observed images (d).



根据相机外参计算需要采样的光路

函数[get_rays]()和[get_rays_np]()

- `H, W`是分辨率
- [内参矩阵]()输入`K = np.array([[focal, 0, 0.5W], [0, focal, 0.5H], [0, 0, 1]])`是焦距之类的
- [外参矩阵]()输入`c2w`表示“Camera-to-world transformation matrix”，一个3x4矩阵
- 输出`rays_o, rays_d`大小都是`(H, W, 3)`分别表示图像上各像素点对应需要采样的光线的原点和方向

函数`render`

```
def render(H, W, K, chunk=1024*32, rays=None, c2w=None, ndc=True,
                  near=0., far=1.,
                  use_viewdirs=False, c2w_staticcam=None,
                  **kwargs):
    """Render rays
    Args:
      H: int. Height of image in pixels.
      W: int. Width of image in pixels.
      focal: float. Focal length of pinhole camera.
      chunk: int. Maximum number of rays to process simultaneously. Used to
        control maximum memory usage. Does not affect final results.
      rays: array of shape [2, batch_size, 3]. Ray origin and direction for
        each example in batch.
      c2w: array of shape [3, 4]. Camera-to-world transformation matrix.
      ndc: bool. If True, represent ray origin, direction in NDC coordinates.
      near: float or array of shape [batch_size]. Nearest distance for a ray.
      far: float or array of shape [batch_size]. Farthest distance for a ray.
      use_viewdirs: bool. If True, use viewing direction of a point in space in
model.
      c2w_staticcam: array of shape [3, 4]. If not None, use this transformation
matrix for
       camera while using other c2w argument for viewing directions.
    Returns:
      rgb_map: [batch_size, 3]. Predicted RGB values for rays.
      disp_map: [batch_size]. Disparity map. Inverse of depth.
      acc_map: [batch_size]. Accumulated opacity (alpha) along a ray.
      extras: dict with everything returned by render_rays().
    """
```

```
    if c2w is not None:
        # special case to render full image
        rays_o, rays_d = get_rays(H, W, K, c2w)
    else:
        # use provided ray batch
        rays_o, rays_d = rays

    if use_viewdirs:
        # provide ray directions as input
        viewdirs = rays_d
        if c2w_staticcam is not None:
            # special case to visualize effect of viewdirs
            rays_o, rays_d = get_rays(H, W, K, c2w_staticcam)
        viewdirs = viewdirs / torch.norm(viewdirs, dim=-1, keepdim=True)
        viewdirs = torch.reshape(viewdirs, [-1,3]).float()

    sh = rays_d.shape # [..., 3]
    if ndc:
        # for forward facing scenes
        rays_o, rays_d = ndc_rays(H, W, K[0][0], 1., rays_o, rays_d)
```

如果输入了`rays`就直接用，否则就用`c2w`或者`c2w_staticcam`算出`rays_o`和`rays_d`。

```
    # Create ray batch
    rays_o = torch.reshape(rays_o, [-1,3]).float()
    rays_d = torch.reshape(rays_d, [-1,3]).float()
```

reshape成Batch。因为计算过程以光线为单位，不需要管光线对应图片上的哪个像素。

```
    near, far = near * torch.ones_like(rays_d[...,:1]), far *
torch.ones_like(rays_d[...,:1])
    rays = torch.cat([rays_o, rays_d, near, far], -1)
    if use_viewdirs:
        rays = torch.cat([rays, viewdirs], -1)
```

这是把`rays`和光线的最近最远距离合并，作为模型的输入。

```
    # Render and reshape
    all_ret = batchify_rays(rays, chunk, **kwargs)
    for k in all_ret:
        k_sh = list(sh[:-1]) + list(all_ret[k].shape[1:])
        all_ret[k] = torch.reshape(all_ret[k], k_sh)

    k_extract = ['rgb_map', 'disp_map', 'acc_map']
    ret_list = [all_ret[k] for k in k_extract]
    ret_dict = {k : all_ret[k] for k in all_ret if k not in k_extract}
    return ret_list + [ret_dict]
```

这是执行推断过程，输出结果。结果为每个像素的颜色和视差。

函数`batchify_rays`

就是根据输入的batch size将输入的`rays`分批调用`render_rays`。

函数`render_rays`

```
def render_rays(ray_batch,
                network_fn,
                network_query_fn,
                N_samples,
                retraw=False,
                lindisp=False,
                perturb=0.,
                N_importance=0,
                network_fine=None,
                white_bkgd=False,
                raw_noise_std=0.,
                verbose=False,
                pytest=False):
    """Volumetric rendering.
    Args:
      ray_batch: array of shape [batch_size, ...]. All information necessary
        for sampling along a ray, including: ray origin, ray direction, min
        dist, max dist, and unit-magnitude viewing direction.
      network_fn: function. Model for predicting RGB and density at each point
        in space.
```

```
      network_query_fn: function used for passing queries to network_fn.
      N_samples: int. Number of different times to sample along each ray.
      retraw: bool. If True, include model's raw, unprocessed predictions.
      lindisp: bool. If True, sample linearly in inverse depth rather than in
depth.
      perturb: float, 0 or 1. If non-zero, each ray is sampled at stratified
        random points in time.
      N_importance: int. Number of additional times to sample along each ray.
        These samples are only passed to network_fine.
      network_fine: "fine" network with same spec as network_fn.
      white_bkgd: bool. If True, assume a white background.
      raw_noise_std: ...
      verbose: bool. If True, print more debugging info.
    Returns:
      rgb_map: [num_rays, 3]. Estimated RGB color of a ray. Comes from fine
model.
      disp_map: [num_rays]. Disparity map. 1 / depth.
      acc_map: [num_rays]. Accumulated opacity along each ray. Comes from fine
model.
      raw: [num_rays, num_samples, 4]. Raw predictions from model.
      rgb0: See rgb_map. Output for coarse model.
      disp0: See disp_map. Output for coarse model.
      acc0: See acc_map. Output for coarse model.
      z_std: [num_rays]. Standard deviation of distances along ray for each
        sample.
    """
```

```
    N_rays = ray_batch.shape[0]
    rays_o, rays_d = ray_batch[:,0:3], ray_batch[:,3:6] # [N_rays, 3] each
    viewdirs = ray_batch[:,-3:] if ray_batch.shape[-1] > 8 else None
    bounds = torch.reshape(ray_batch[...,6:8], [-1,1,2])
    near, far = bounds[...,0], bounds[...,1] # [-1,1]

    t_vals = torch.linspace(0., 1., steps=N_samples)
    if not lindisp:
        z_vals = near * (1.-t_vals) + far * (t_vals)
    else:
        z_vals = 1./(1./near * (1.-t_vals) + 1./far * (t_vals))

    z_vals = z_vals.expand([N_rays, N_samples])

    if perturb > 0.:
        # get intervals between samples
        mids = .5 * (z_vals[...,1:] + z_vals[...,:-1])
        upper = torch.cat([mids, z_vals[...,-1:]], -1)
        lower = torch.cat([z_vals[...,:1], mids], -1)
        # stratified samples in those intervals
        t_rand = torch.rand(z_vals.shape)

        # Pytest, overwrite u with numpy's fixed random numbers
        if pytest:
            np.random.seed(0)
            t_rand = np.random.rand(*list(z_vals.shape))
            t_rand = torch.Tensor(t_rand)
```

```
        z_vals = lower + (upper - lower) * t_rand

    pts = rays_o[...,None,:] + rays_d[...,None,:] * z_vals[...,:,None] # [N_rays, N_samples, 3]
```

这是在输入的光路上生成`N_samples`个采样点。

```
#     raw = run_network(pts)
    raw = network_query_fn(pts, viewdirs, network_fn)
    rgb_map, disp_map, acc_map, weights, depth_map = raw2outputs(raw, z_vals, rays_d, raw_noise_std, white_bkgd, pytest=pytest)
```

这是调用DNN推断输出计算结果。`network_query_fn`是外面输入的模型推断函数，输入是每条光线上的每个采样点位置，输出是每条光线的各离散采样区间δ_n内的颜色c_n和粒子密度σ_n；`raw2outputs`是将模型输出进行积分得到每条光线的颜色。

```
    if N_importance > 0:

        rgb_map_0, disp_map_0, acc_map_0 = rgb_map, disp_map, acc_map

        z_vals_mid = .5 * (z_vals[...,1:] + z_vals[...,:-1])
        z_samples = sample_pdf(z_vals_mid, weights[...,1:-1], N_importance, det=(perturb==0.), pytest=pytest)
        z_samples = z_samples.detach()

        z_vals, _ = torch.sort(torch.cat([z_vals, z_samples], -1), -1)
        pts = rays_o[...,None,:] + rays_d[...,None,:] * z_vals[...,:,None] # [N_rays, N_samples + N_importance, 3]

        run_fn = network_fn if network_fine is None else network_fine
#         raw = run_network(pts, fn=run_fn)
        raw = network_query_fn(pts, viewdirs, run_fn)

        rgb_map, disp_map, acc_map, weights, depth_map = raw2outputs(raw, z_vals, rays_d, raw_noise_std, white_bkgd, pytest=pytest)
```

这多算几次?

```
    ret = {'rgb_map' : rgb_map, 'disp_map' : disp_map, 'acc_map' : acc_map}
    if retraw:
        ret['raw'] = raw
    if N_importance > 0:
        ret['rgb0'] = rgb_map_0
        ret['disp0'] = disp_map_0
        ret['acc0'] = acc_map_0
        ret['z_std'] = torch.std(z_samples, dim=-1, unbiased=False)  # [N_rays]

    for k in ret:
        if (torch.isnan(ret[k]).any() or torch.isinf(ret[k]).any()) and DEBUG:
            print(f"! [Numerical Error] {k} contains nan or inf.")

    return ret
```

函数raw2outputs

```
def raw2outputs(raw, z_vals, rays_d, raw_noise_std=0, white_bkgd=False,
pytest=False):
    """Transforms model's predictions to semantically meaningful values.
    Args:
        raw: [num_rays, num_samples along ray, 4]. Prediction from model.
        z_vals: [num_rays, num_samples along ray]. Integration time.
        rays_d: [num_rays, 3]. Direction of each ray.
    Returns:
        rgb_map: [num_rays, 3]. Estimated RGB color of a ray.
        disp_map: [num_rays]. Disparity map. Inverse of depth map.
        acc_map: [num_rays]. Sum of weights along each ray.
        weights: [num_rays, num_samples]. Weights assigned to each sampled color.
        depth_map: [num_rays]. Estimated distance to object.
    """
```

输入的`raw`是每条光线上各离散采样区间内颜色和概率密度，即DNN的输出、`z_vals`是每条光线上每个采样区间的长度、`rays_d`是每条光线的方向。

主要输出`rgb_map`是每条光线的颜色、`disp_map`是每条光线的视差、`depth_map`是每条光线的深度。

```
    raw2alpha = lambda raw, dists, act_fn=F.relu: 1.-torch.exp(-
act_fn(raw)*dists)
```

`raw2alpha`对应体渲染公式中的$1-e^{-\sigma_n\delta_n}$。

```
    dists = z_vals[...,1:] - z_vals[...,:-1]
    dists = torch.cat([dists, torch.Tensor([1e10]).expand(dists[...,:1].shape)],
-1)  # [N_rays, N_samples]
```

每条光线的离散采样区间从0开始计算距离。

```
    dists = dists * torch.norm(rays_d[...,None,:], dim=-1)
```

这个应该是归一化之类的操作。

```
    rgb = torch.sigmoid(raw[...,:3])  # [N_rays, N_samples, 3]
```

看来`raw[...,:3]`里面就是每个采样点的颜色数据。

```
    noise = 0.
    if raw_noise_std > 0.:
        noise = torch.randn(raw[...,3].shape) * raw_noise_std

        # Overwrite randomly sampled data if pytest
        if pytest:
            np.random.seed(0)
            noise = np.random.rand(*list(raw[...,3].shape)) * raw_noise_std
            noise = torch.Tensor(noise)
```

测试时可以加噪声。

```
    alpha = raw2alpha(raw[...,3] + noise, dists)  # [N_rays, N_samples]
```

算$1-e^{-\sigma_n\delta_n}$。

```
    # weights = alpha * tf.math.cumprod(1.-alpha + 1e-10, -1, exclusive=True)
    weights = alpha * torch.cumprod(torch.cat([torch.ones((alpha.shape[0], 1)),
1.-alpha + 1e-10], -1), -1)[:, :-1]
```

这里`torch.cumprod`是在算$T_n=e^{-\sum_{k=1}^{n-1}\sigma_k\delta_k}$，`weights`对应的是$T_n\left(1-e^{-\sigma_n\delta_n}\right)$。

```
    rgb_map = torch.sum(weights[...,None] * rgb, -2)  # [N_rays, 3]
```

积分求颜色，一看就懂。

```
    depth_map = torch.sum(weights * z_vals, -1)
    disp_map = 1./torch.max(1e-10 * torch.ones_like(depth_map), depth_map /
torch.sum(weights, -1))
    acc_map = torch.sum(weights, -1)

    if white_bkgd:
        rgb_map = rgb_map + (1.-acc_map[...,None])

    return rgb_map, disp_map, acc_map, weights, depth_map
```

计算每条光线的深度`depth_map`和视差`disp_map`，还把`weights`求了个和作为`acc_map`。
在最后的输出中，这里几个东西都没用上，训练过程只用了颜色`rgb`与Groung-truth求差。