Neural Radiance Field, Language Guidance and Robotic Manipulation

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Dec 15, 2023

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Outline

Neural Radiance Field

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis[1]

- Input: (x, y, z, θ, ϕ)
- Output: (r, g, b, σ)
- MLP: $F_\theta : (x, y, z, \theta, \phi) \rightarrow (r, g, b, \sigma)$

[1] ECCV 2020 Oral - Best Paper Honorable Mention

What Can NeRF Representation Do?

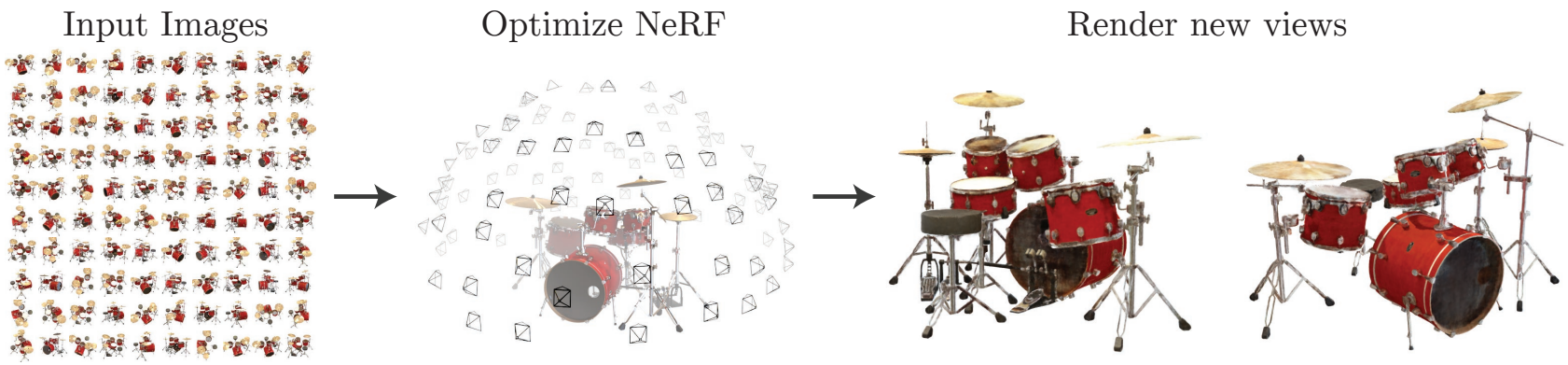
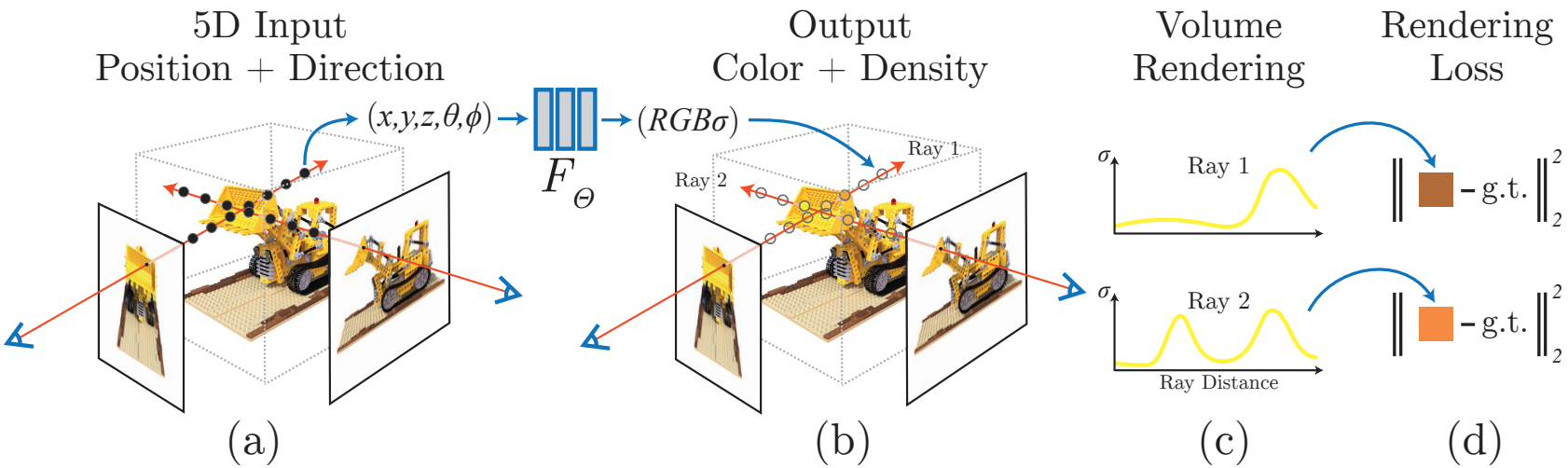


Figure: Optimize from a set of input images and render novel views

How to Optimize

- Given: a set of captured RGB images of the scene
- Volume Rendering: 5D radiance field $\rightarrow$ RGB images
- Loss: $\mathcal{L} = \sum_{\mathbf{r}\in\mathcal{R}}[\|\hat{C}_c(\mathbf{r}) - C(\mathbf{r})\|_2^2 + \|\hat{C}_f(\mathbf{r}) - C(\mathbf{r})\|_2^2]$

NeRF Overview



Volume Rendering with Radiance Fields

- NeRF output: $(\mathbf{c}(\mathbf{x}, \mathbf{d}), \sigma(\mathbf{x}))$
- Expected color:

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t), \mathbf{d})\ dt \tag{1}$$

- Accumulated transmittance:

$$T(t) = \exp(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))\ ds \tag{2}$$

Numerical Estimation

- Stratified sampling:

$$t_i \sim \mathcal{U}\left[t_n + \frac{i-1}{N}(t_f - t_n),\ \ t_n + \frac{i}{N}(t_f - t_n)\right] \tag{3}$$

- Approximated color:

$$\hat{C}(\mathbf{r}) = \sum_{i=1}^{N} T_i(1 - \exp(-\sigma_i \delta_i))\mathbf{c}_i \tag{4}$$

where

$$T_i = \exp(-\sum_{j=1}^{i-1} \sigma_j \delta_j),\ \ \delta_i = t_{i+1} - t_i$$

Volume Rendering Digest

- Differential probability (reparameterization):

$$\sigma(\mathbf{x}) \rightarrow \sigma(t)$$

given $\mathbf{r} = (\mathbf{o}, \mathbf{d})$, $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$

- Transmittance:

$$T(t + dt) = T(t) \cdot (1 - dt \cdot \sigma(t)) \tag{5}$$

Transmittance

$$T(t+dt) = T(t) \cdot (1 - dt \cdot \sigma(t))$$

$$\frac{T(t+dt) - T(d)}{dt} \equiv T'(t) = -T(t)\sigma(t)$$

Solve this classical differential equation as follows:

$$T'(t) = -T(t)\sigma(t)$$

$$\int_a^b \frac{T'(t)}{T(t)} dt = -\int_a^b \sigma(t)\ dt$$

$$\log T(t)\Big|_a^b = -\int_a^b \sigma(t)\ dt \tag{6}$$

$$T(a \to b) \equiv \frac{T(b)}{T(a)} = \exp(-\int_a^b \sigma(t)\ dt)$$

Homogeneous Media

- constant $\mathbf{c}_a$, σ_a over a ray segment $[a, b]$

$$
\begin{aligned}
\mathbf{C}(a \to b) &= \int_a^b T(a \to t) \cdot \sigma(t) \cdot \mathbf{c}(t)\, dt \\
&= \sigma_a \cdot \mathbf{c}_a \int_a^b T(a \to t)\, dt \\
&= \sigma_a \cdot \mathbf{c}_a \int_a^b \exp(-\int_a^t \sigma(u)\, du)\, dt \\
&= \sigma_a \cdot \mathbf{c}_a \int_a^b \exp(-\sigma_a(t-a))\, dt \\
&= \sigma_a \cdot \mathbf{c}_a \cdot \frac{\exp(-\sigma_a(t-a))}{-\sigma_a}\Bigg|_a^b \\
&= \mathbf{c}_a \cdot (1 - \exp(-\sigma_a(b-a))
\end{aligned}
\tag{7}
$$

Transmittance Is Multiplicative

$$
\begin{aligned}
T(a \to c) &= \exp\left(- \int_a^c \sigma(t)\, dt \right) \\
&= \exp\left(- \left[\int_a^b \sigma(t)\, dt + \int_b^c \sigma(t)\, dt \right] \right) \\
&= \exp\left(- \int_a^b \sigma(t)\, dt \right) \exp\left(- \int_b^c \sigma(t)\, dt \right) \\
&= T(a \to b) \cdot T(b \to c)
\end{aligned}
\tag{8}
$$

Transmittance for Piecewise Constant Data

- Given: $\{[t_i, t_{i+1}]\}_{i=1}^{N}$, $t_1 = 0$, $\delta_i = t_{i+1} - t_i$
- Constant: σ_i

$$
\begin{aligned}
T_i = T(t_i) = T(0 \to t_i) &= \exp\left(- \int_0^{t_i} \sigma(t)\, dt \right) \\
&= \exp\left(\sum_{j=1}^{i-1} -\sigma_j \delta_j \right)
\end{aligned}
\tag{9}
$$

Volume Rendering of Piecewise Constant Data

$$
\begin{aligned}
\mathbf{C}(t_{N+1}) &= \sum_{i=1}^{N} \int_{t_i}^{t_{i+1}} T(t) \cdot \sigma_i \cdot \mathbf{c}_i \, dt \\
&= \sum_{i=1}^{N} \int_{t_i}^{t_{i+1}} T(0 \to t_i) \cdot T(t_i \to t) \cdot \sigma_i \cdot \mathbf{c}_i \, dt \\
&= \sum_{i=1}^{N} T(0 \to t_i) \int_{t_i}^{t_{i+1}} T(t_i \to t) \cdot \sigma_i \cdot \mathbf{c}_i \, dt \qquad \text{constant} \\
&= \sum_{i=1}^{N} T(0 \to t_i) \cdot (1 - \exp(-\sigma_i(t_{i+1} - t_i))) \cdot \mathbf{c}_i \qquad \text{from (7)}
\end{aligned}
$$

Volume Rendering from NeRF

$$\mathbf{C}(t_{N+1}) = \sum_{i=1}^{N} T_i \cdot (1 - \exp(-\sigma_i \delta_i)) \cdot \mathbf{c}_i, \tag{10}$$

where

$$T_i = \exp(-\sum_{j=1}^{i-1} \sigma_j \delta_j), \quad \delta_i = t_{i+1} - t_i$$

re-express:

$$\mathbf{C}(t_{N+1}) = \sum_{i=1}^{N} T_i \cdot \alpha_i \cdot \mathbf{c}_i \tag{11}$$

where

$$\alpha_i \equiv 1 - \exp(-\sigma_i \delta_i)$$

Volume Rendering in Practice

nerf demo

```
# Run network
pts_flat = tf.reshape(pts, [-1,3])
pts_flat = embed_fn(pts_flat)
raw = batchify(network_fn)(pts_flat)
raw = tf.reshape(raw, list(pts.shape[:-1]) + [4])

# Compute opacities and colors
sigma_a = tf.nn.relu(raw[...,3])
rgb = tf.math.sigmoid(raw[...,:3])

# Do volume rendering
dists = tf.concat([z_vals[..., 1:] - z_vals[..., :-1], tf.broadcast_to([1e10], z_vals[...,:1].shape)], -1)
alpha = 1.-tf.exp(-sigma_a * dists)
weights = alpha * tf.math.cumprod(1.-alpha + 1e-10, -1, exclusive=True)

rgb_map = tf.reduce_sum(weights[...,None] * rgb, -2)
depth_map = tf.reduce_sum(weights * z_vals, -1)
acc_map = tf.reduce_sum(weights, -1)
```

NeRF Core Optimization Loop

```
with tf.GradientTape() as tape:
    # Make predictions for color, disparity, accumulated opacity.
    rgb, disp, acc, extras = render(
        H, W, focal, chunk=args.chunk, rays=batch_rays,
        verbose=i < 10, retraw=True, **render_kwargs_train)
    # Compute MSE loss between predicted and true RGB.
    img_loss = img2mse(rgb, target_s)
    trans = extras['raw'][..., -1]
    loss = img_loss
    psnr = mse2psnr(img_loss) # peak signal to noise ratio
    # Add MSE loss for coarse-grained model
    if 'rgb0' in extras:
        img_loss0 = img2mse(extras['rgb0'], target_s)
        loss += img_loss0
        psnr0 = mse2psnr(img_loss0)

gradients = tape.gradient(loss, grad_vars)
optimizer.apply_gradients(zip(gradients, grad_vars))
```

How Did NeRF and VLMs Get Married?

Decomposing NeRF for Editing via Feature Field Distillation[2]

- Editing a scene represented by a NeRF is challenging
- Semantic scene decomposition? 3D feature field
- Distill the knowledge of VLMs

[2] NeurIPS 2022

Distilled Feature Field

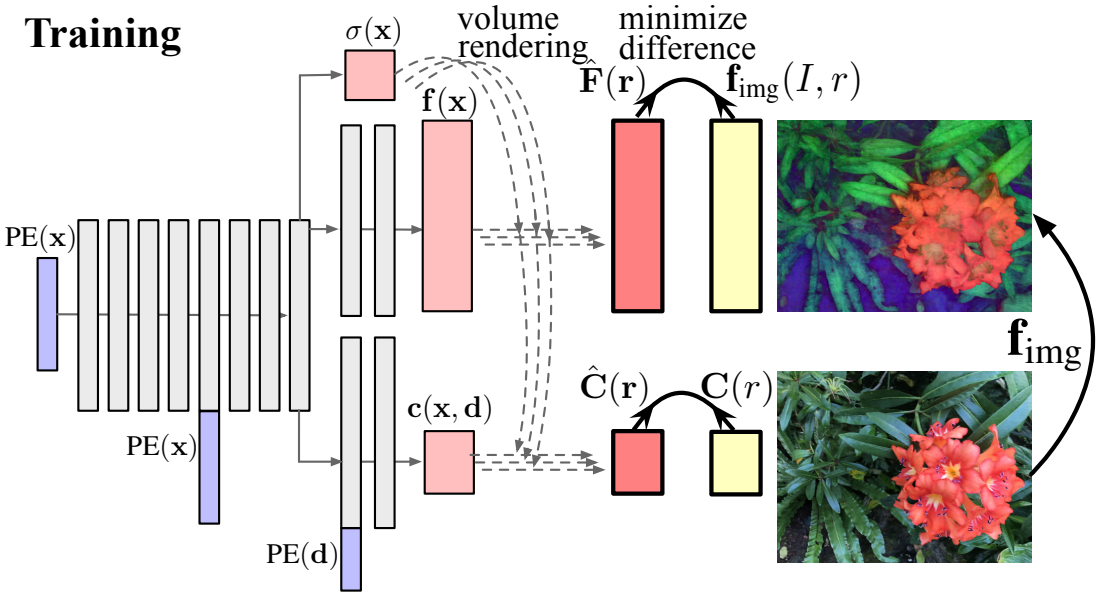
- Maps from $(\mathbf{x}, \mathbf{d})$ to $(\mathbf{c}(\mathbf{x}, \mathbf{d}), \sigma(\mathbf{x}), \mathbf{f}(\mathbf{x}))$
- Volume Rendering

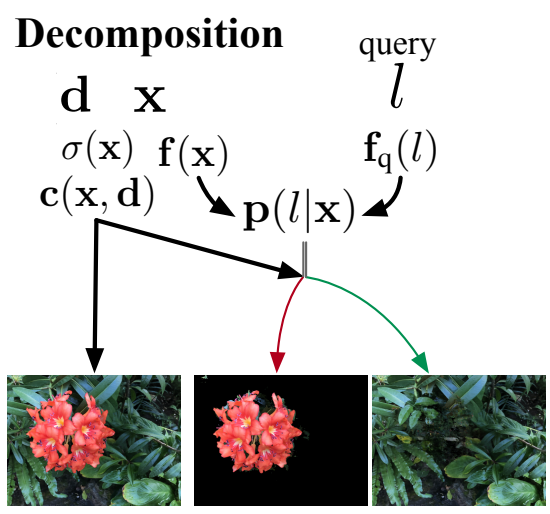
$$\hat{\mathbf{F}}(\mathbf{r}) = \sum_{k=1}^{K} \hat{T}(t_k)\alpha(\sigma_k\delta_k)\mathbf{f}(\mathbf{x}_k) \tag{12}$$

- Loss

$$\begin{aligned} L &= L_p + \lambda L_f \\ L_p &= \sum_{\mathbf{r}\in\mathcal{R}} \left|\left|\hat{\mathbf{C}}(\mathbf{r}) - \mathbf{C}(r)\right|\right|_2^2 \\ L_f &= \sum_{\mathbf{r}\in\mathcal{R}} \left|\left|\hat{\mathbf{F}}(\mathbf{r}) - \mathbf{f}_{\mathtt{img}}(I, r)\right|\right|_1 \end{aligned} \tag{13}$$

Feature Field Distillation





$$\mathbf{p}(l|\mathbf{x}) = \frac{\exp(\mathbf{f}(\mathbf{x})\mathbf{f}_{\text{q}}(l)^T)}{\sum_{l' \in \mathcal{L}} \exp(\mathbf{f}(\mathbf{x})\mathbf{f}_{\text{q}}(l')^T)} \tag{14}$$

Pseudo Code for MaskCLIP

Extract Free Dense Labels from CLIP[3]

Algorithm 1 Image Feature (Original)

```
def forward(x):
  q, k, v = W_qkv @ self.ln_1(x)
  v = (q[:1] * k).softmax(dim=-1) * v
  x = x + W_out @ v
  x = x + self.mlp(self.ln_2(x))
  return x[:1]    # the CLS token
```

Algorithm 2 Dense Features (MaskCLIP 11)

```
def forward(x):
  v = W_v @ self.ln_1(x)
  z = W_out @ v
  return z[1:] # all but the CLS token
```

[3] ECCV 2022

CLIP for Patch-level Feature

```python
def forward_v(self, x: torch.Tensor):
    """
    Forward function for computing the value features for dense prediction
    (i.e., features for every image patch).
    """
    v_in_proj_weight = self.attn.in_proj_weight[-self.attn.embed_dim:]
    v_in_proj_bias = self.attn.in_proj_bias[-self.attn.embed_dim:]
    # raw_images [3, 3, 336, 597], patch_size: 14, tokenized [3, 24, 42, embed_dim]
    v_in = F.linear(self.ln_1(x), v_in_proj_weight, v_in_proj_bias)
    v_out = F.linear(v_in, self.attn.out_proj.weight, self.attn.out_proj.bias)
    return v_out  # pz note: [1009, 3, 1024] , 1009 = 24 * 42 + 1
```

Pixel, Ray and Patch

- Sample pixels then generate ray[4]

```
def next_train(self, step: int) -> Tuple[RayBundle, Dict]:
    """Returns the next batch of data from the train dataloader."""
    self.train_count += 1
    image_batch = next(self.iter_train_image_dataloader)
    assert self.train_pixel_sampler is not None
    assert isinstance(image_batch, dict)
    batch = self.train_pixel_sampler.sample(image_batch)
    ray_indices = batch["indices"]
    ray_bundle = self.train_ray_generator(ray_indices)
    return ray_bundle, batch
```

[4] nerfstudio

Pixel, Ray and Patch

- From pixel index to patch index

```python
def next_train(self, step: int) -> Tuple[RayBundle, Dict]:
    """Nearest neighbor interpolation of features"""
    ray_bundle, batch = super().next_train(step)
    ray_indices = batch["indices"]
    camera_idx = ray_indices[:, 0]
    y_idx = (ray_indices[:, 1] * self.scale_h).long()
    x_idx = (ray_indices[:, 2] * self.scale_w).long()
    batch["feature"] = self.train_features[camera_idx, y_idx, x_idx]
    # (4096, 768) === (N_rays, feature_dim)
    return ray_bundle, batch
```

Bridge 2D-to-3D Gap for Robotic Manipulation

Distilled Feature Fields Enable Few-Shot Language-Guided Manipulation [5]

- DFFs: 3D geometry + rich semantics from 2D VLMs
- 6-DOF grasp or palce pose: $\mathbf{T} = (\mathbf{R}, \mathbf{t})$
- Few-shot manipulation: $< \{\mathbf{I}\}, \mathbf{T}^* >, \ \{\mathbf{I}\}_{i=1}^{N}$
- Open-text language-guided manipulation: $L^+, \ L^-$

[5] CoRL 2023 - Best Paper

Transformation Explained

- SE(3): Special Euclidean group in 3 dimensions
- Rotation matrix example

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix}$$

- Translation

$$(x, y, z) \xrightarrow{(a,b,c)} (x + a, y + b, z + c)$$

Representing 6-DOF Poses with Feature Fields

- Approximate **local** 3D feature field via query points

$$\mathcal{X} = \{\mathbf{x} \in \mathbb{R}^3\}_{N_q}$$

- α-*weighted features*

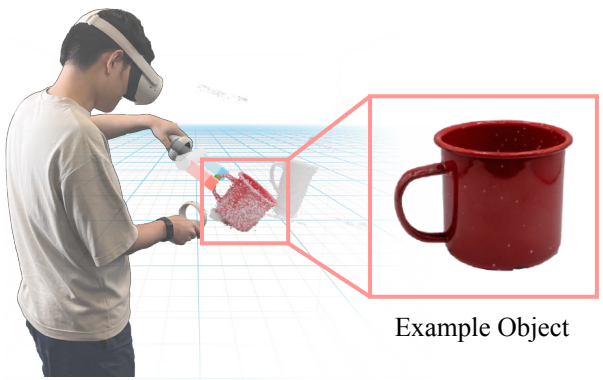
$$\mathbf{f}_\alpha(\mathbf{x}) = \alpha(\mathbf{x}) \cdot \mathbf{f}(\mathbf{x}),\ \alpha(\mathbf{x}) = 1 - \exp(-\sigma(\mathbf{x}) \cdot \delta)$$

- Demo pose $\mathbf{T}$ representation: sample and concatenate

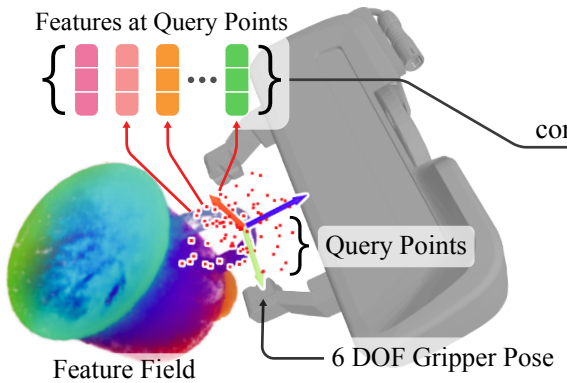
$$\{\mathbf{f}_\alpha(\mathbf{x}) \mid \mathbf{x} \in \mathbf{T}\mathcal{X}\},\ \ \mathbf{z}_\mathbf{T} \in \mathbb{R}^{N_\mathbf{q} \cdot |\mathbf{f}|}$$

A More Concrete View

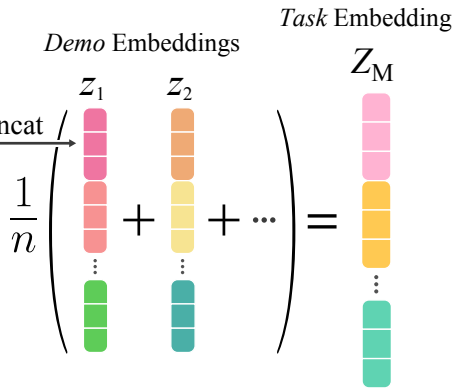
query points $\xrightarrow{\text{sampling}}$ features $\xrightarrow{\text{concat}}$ demo embed $\xrightarrow{\text{avg}}$ task embed



(a) Collect Demonstrations in VR



(b) Sample Feature Vectors



(c) Average Over n Demos

Inferring 6-DOF Poses

- Coarse pre-filtering
  - geometric: $\alpha(\mathbf{v}) < \epsilon_{\text{free}} = 0.1$
  - semantic: $\cos(\mathbf{f}_\alpha(\mathbf{v}), \mathbf{Z}_M) < \epsilon_{\text{task}}$
- Pose optimization

$$\mathcal{T} = \{T\}$$

$$\mathcal{J}_{\text{pose}}(\mathbf{T}) = -\cos(\mathbf{z}_\mathbf{T}, \mathbf{Z}_M) \tag{15}$$

Open-Text Language-Guided Manipulation

- Retrieving relevant demonstrations

$$\cos(\mathbf{q}, \mathbf{F}_d), \quad \mathbf{q} = \text{emb}_{\text{CLIP}}(L^+)$$

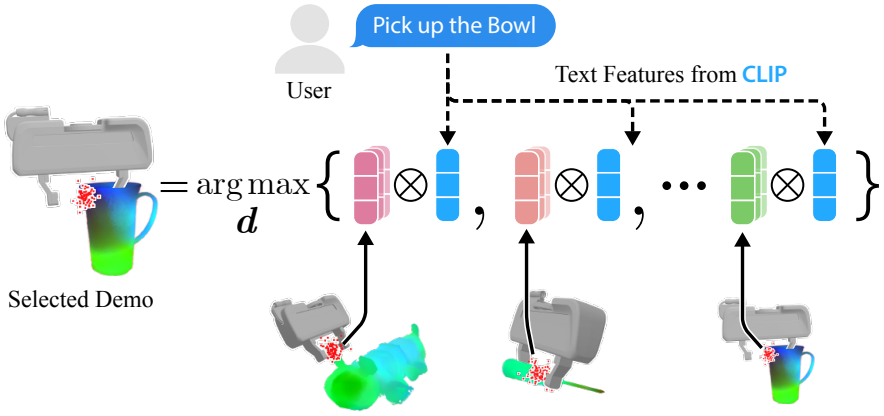
- Initializing grasp proposals

$$\mathbf{q}_i^- = \text{emb}_{\text{CLIP}}(L_i^-) \mid i \in \{i, \cdots, n\}$$

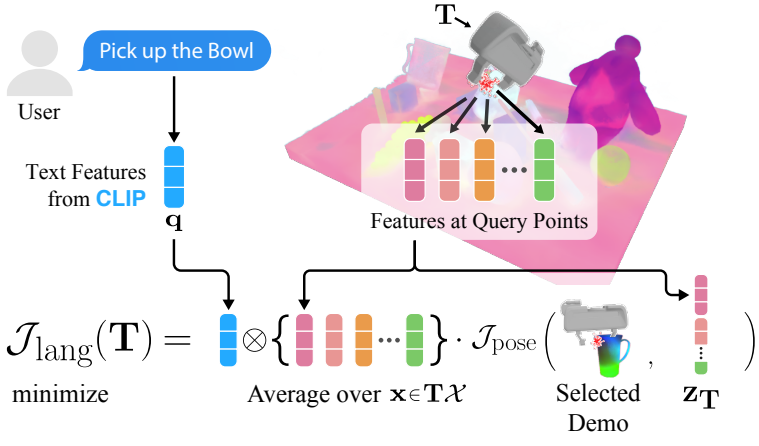
- Language-guided grasp pose optimization

$$\mathcal{J}_{\text{lang}}(\mathbf{T}) = \text{mean}_{\mathbf{x} \in \mathbf{T}} \mathcal{X} \left[\mathbf{q} \otimes \mathbf{f}_\alpha(\mathbf{x}) \right] \cdot \mathcal{J}_{\text{pose}}(\mathbf{T}) \tag{16}$$

Pipeline for Language-Guided Manipulation



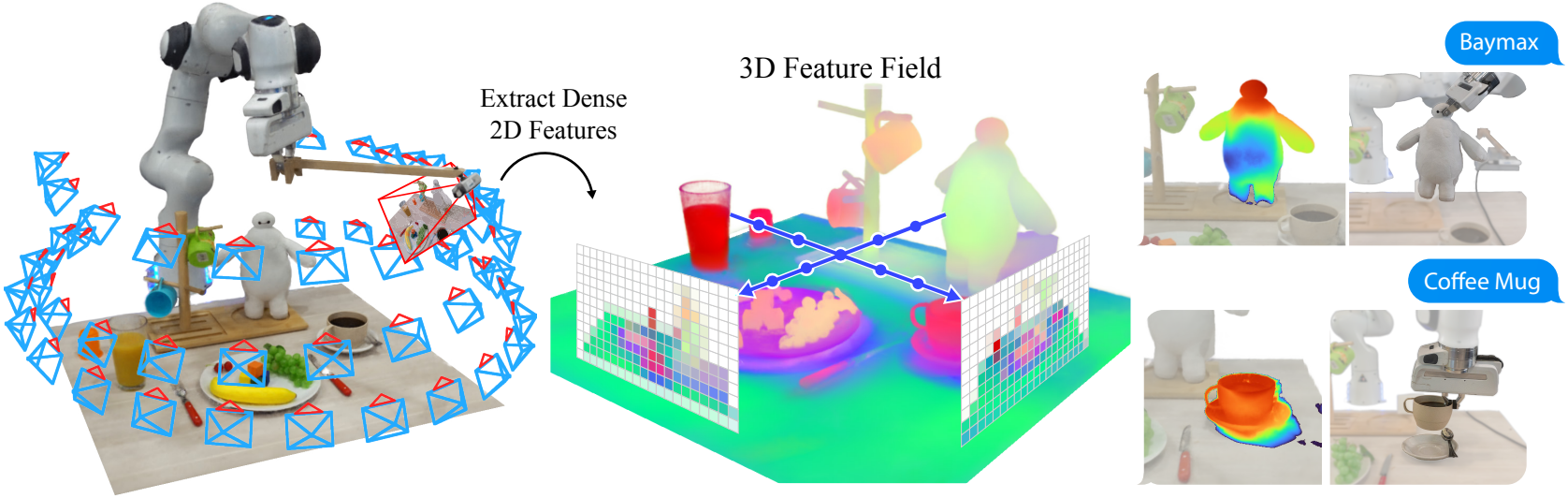
(a) Retrieving Demonstrations



(b) Language-Guided Pose Optimization

F3RM Overview

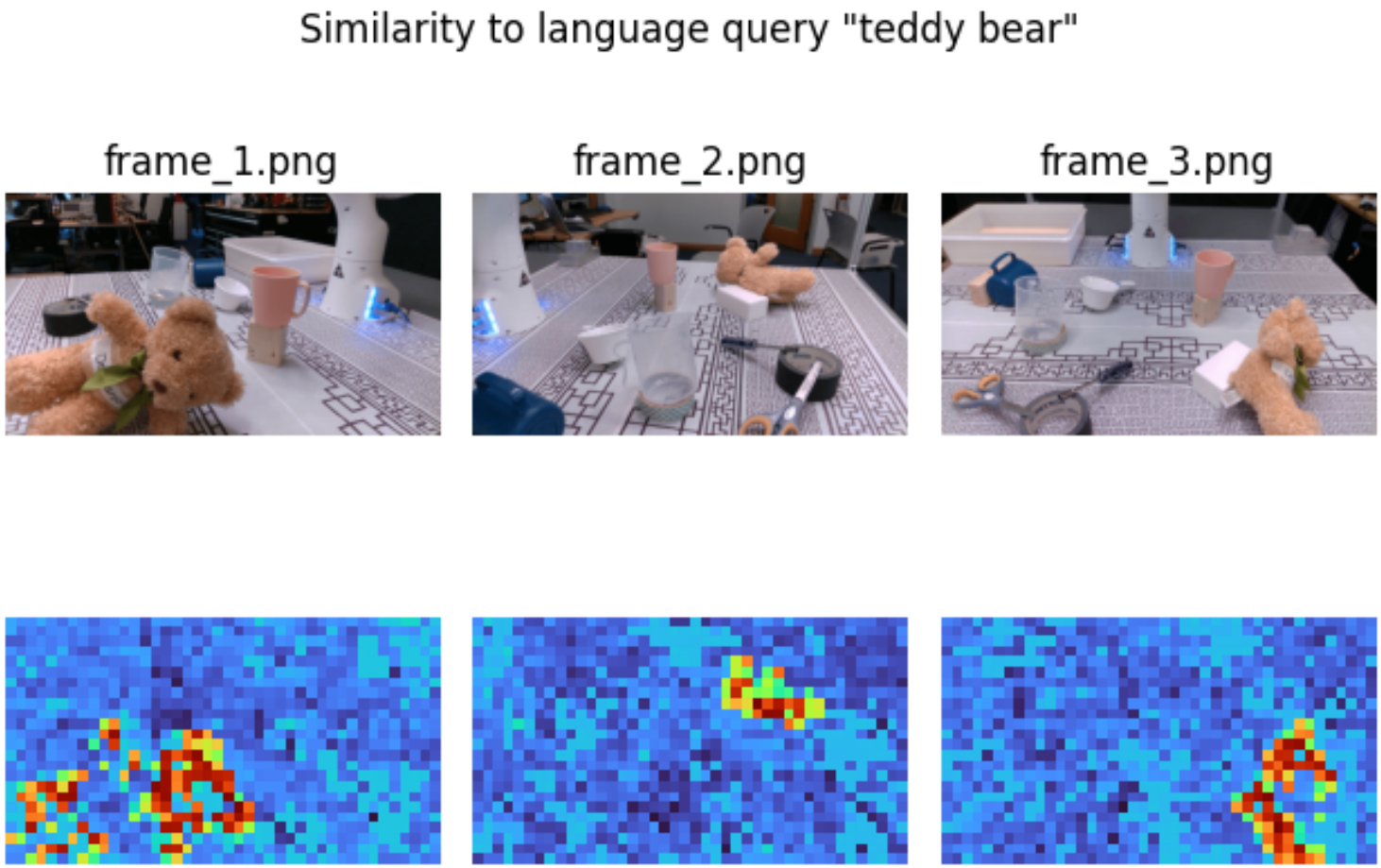
- Collecting multiple images of the scene
- Train a feature field
- Optimize grasp poses using language query and execute



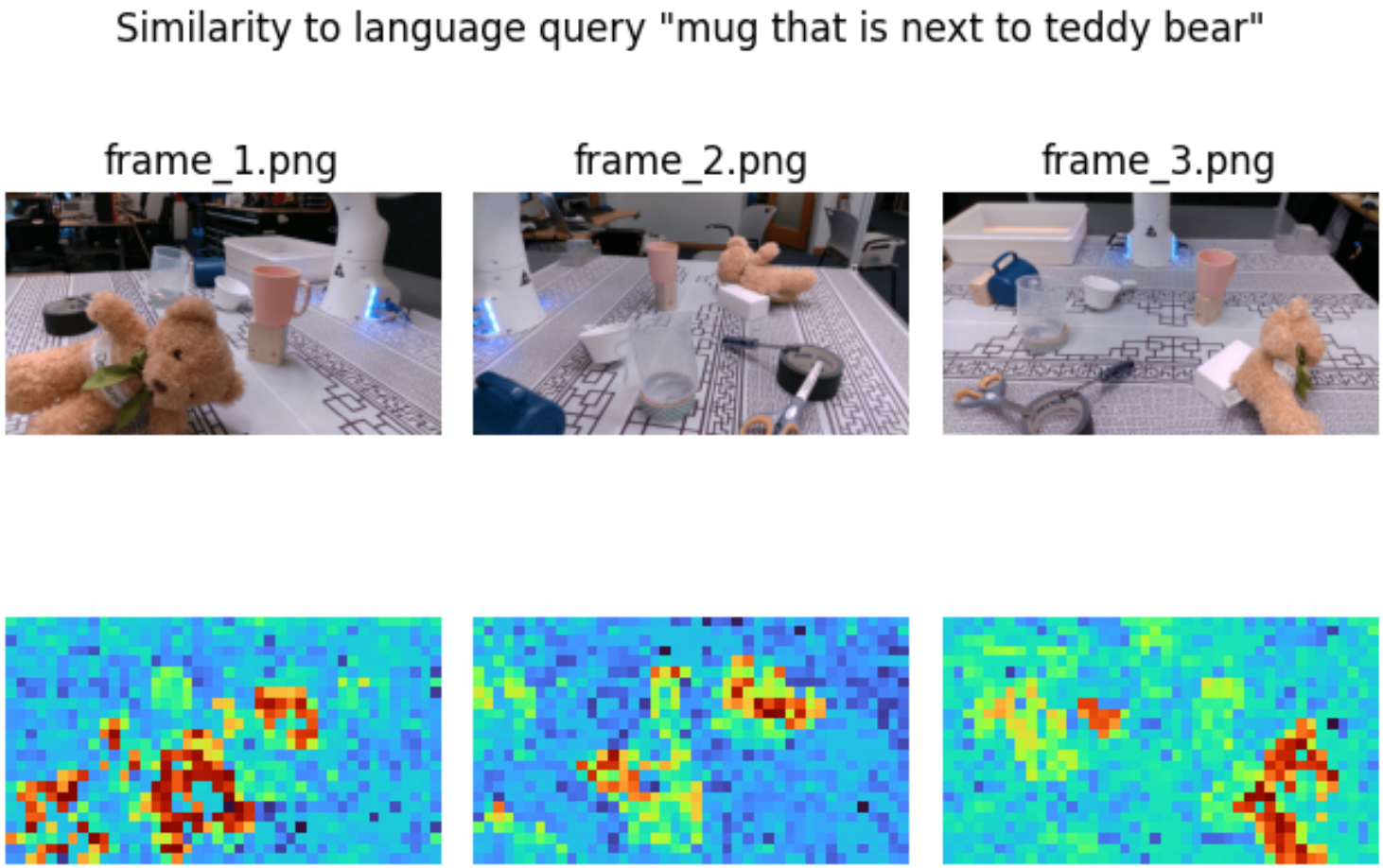
Limitations

- Vision-language models may behave like bag-of-words [1]
- No incentives for model to learn compositional relations between objects.
- Lack of higher-level scene representation[2]

Limitations: Example



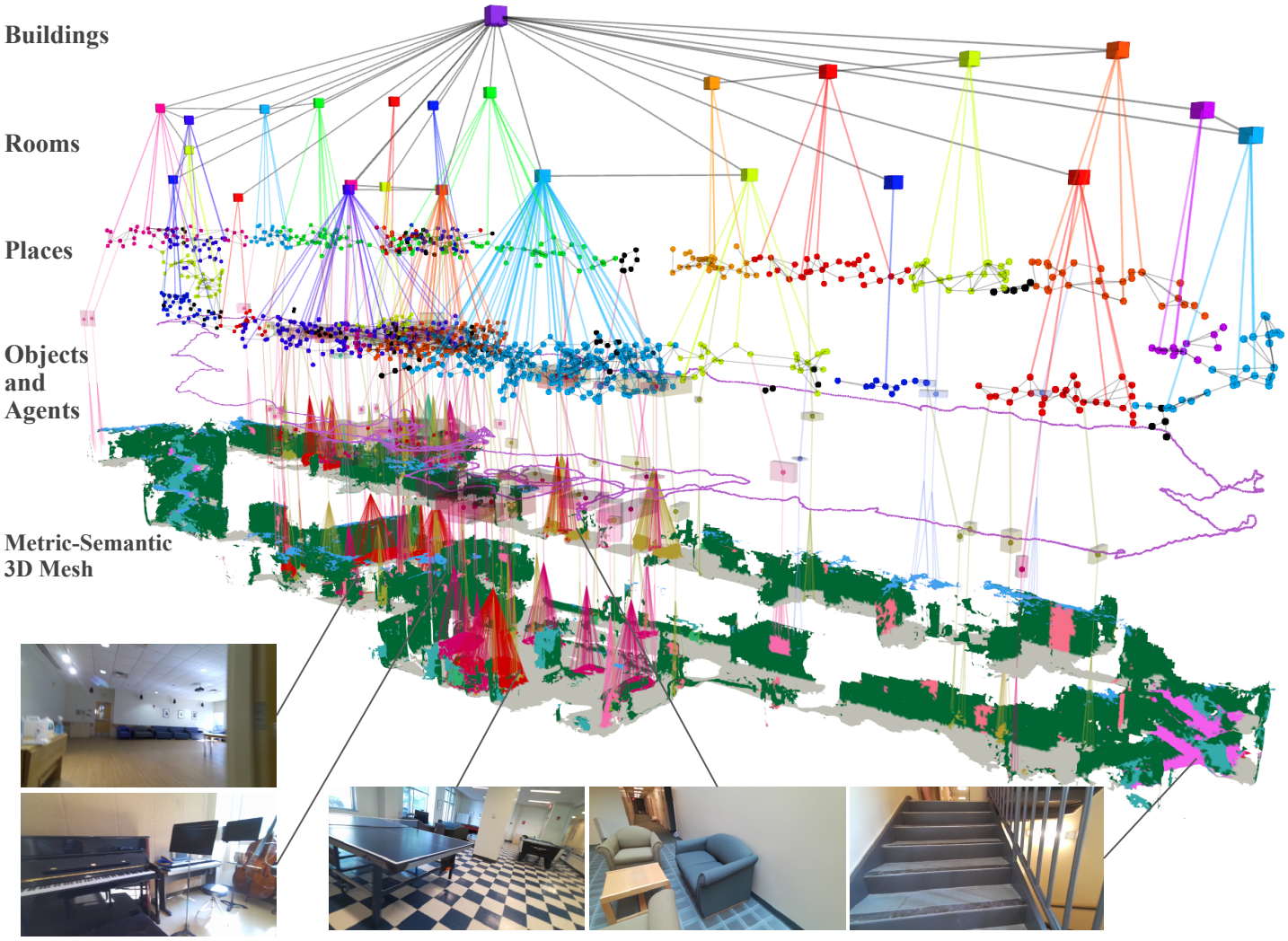
Limitations: Example



Follow-up Questions

- Scene representation at different level [2]?
- Better **scene understanding**? Scene graph?
- Imitation or reinforcement learning?
- Datasets and experimental environment?

3D Scene Graph: A High-level Representation [3]



Simulation Environment

- Available Physics Engine
  - MuJoCo (**Mu**lti-**Jo**int dynamics with **Co**ntact)
  - MetaWorld
  - PyBullet
- Demo

References

[1] **ICLR 2023** - When and why vision-language models behave like bag-of-words models, and what to do about it?

[2] **CoRL 2022** - A Dual Representation Framework for Robot Learning with Human Guidance.

[3] **RSS 2022** - Hydra: A real-time spatial perception system for 3D scene graph construction and optimization.

Thank you very much!
Q&A