3DV-2023 Assignment: Single View to 3D

> PDF provides index navigation. You can utilize it to navigate to the part you want to read.

Goal

In this assignment, you will explore the types of loss and decoder functions for regressing to voxels, and point clouds representation from single view RGB input.

Detailed explanation of your code

Dataset

> Read images and point clouds/voxels from files.
>
> The code I changed:
>
> 1. Remove unused code comments
> 2. Remove permuting image shape from (B, C, H, W) to (B, H, W, C)
>
>   In torch tensor's common format, it is (B, C, H, W).
>
>   In this training flow, I find only the model use the images, and it also permutes back to (B, C, H, W).
>
>   So, It is unnecessary.
>
> Point cloud format: (B, N, 3)
> N: number of points in one image
> 3: xyz coordinate in 3D space.

> Voxel format: binary format, (B, A, B, C)
> A, B, C: the size of voxels (D, H, W)

```python
class ShapeNetDB(Dataset):
    def __init__(self, data_dir: str, data_type: str, n_points: int = 2048):
        super().__init__()
        self.data_dir = data_dir
        self.data_type = data_type
        self.n_points = n_points
        self.db = self.load_db()

        self.get_index()

    def __len__(self):
        return len(self.db)

    def __getitem__(self, idx):
        if self.data_type == "point":
            """
            Return shapes:
            img: (B, 256, 256, 3)
            pc: (B, 2048, 3)
            object_id: (B,)
            """
            img, img_id = self.load_img(idx)
            pc, object_id = self.load_point(idx)

            assert img_id == object_id

            return img, pc, object_id

        elif self.data_type == "voxel":
            """
            Return shapes:
            img: (B, 256, 256, 3)
            voxel: (B, 33, 33, 33)
            object_id: (B,)
            """
            img, img_id = self.load_img(idx)
            voxel, object_id = self.load_voxel(idx)

            assert img_id == object_id

            return img, voxel, object_id

    def load_db(self):
        db_list = sorted(glob.glob(os.path.join(self.data_dir, "*")))

        return db_list

    def get_index(self):
        self.id_index = self.data_dir.split("/").index("data") + 2

    def load_img(self, idx):
        path = os.path.join(self.db[idx], "view.png")
```

```
        img = read_image(path) / 255.0

        object_id = self.db[idx].split("/")[self.id_index]

        return img, object_id

    def load_point(self, idx):
        path = os.path.join(self.db[idx], "point_cloud.npy")
        points: np.ndarray = np.load(path)

        # resample
        # if self.n_points < points.shape[0]:
        #     choice = np.random.choice(points.shape[0], self.n_points,
replace=False)
        #     points = points[choice]

        # normalize
        points -= np.mean(points, axis=0, keepdims=True)  # center
        dist = np.max(np.sqrt(np.sum(points**2, axis=1)), 0)
        points = points / dist  # scale

        object_id = self.db[idx].split("/")[self.id_index]

        return torch.from_numpy(points), object_id

    def load_voxel(self, idx):
        path = os.path.join(self.db[idx], "voxel.npy")
        voxel = np.load(path)

        object_id = self.db[idx].split("/")[self.id_index]

        return torch.from_numpy(voxel).float(), object_id
```

Loss

> voxel_loss: Binary cross entropy with logits (contain sigmoid function)
>
> chamfer_loss: Use the nearest points to calculate loss.
>
> $d_{CD}(X,Y) = \sum_{x \in X} \min_{y \in Y} ||x-y||_2^2 + \sum_{y \in Y} \min_{x \in X} ||x-y||_2^2$

```
def voxel_loss(voxel_src: torch.Tensor, voxel_tgt: torch.Tensor):
    loss = binary_cross_entropy_with_logits(voxel_src, voxel_tgt)
    return loss


def chamfer_loss(point_cloud_src: torch.Tensor, point_cloud_tgt: torch.Tensor):
    assert point_cloud_src.ndimension() == 3  # (B, N, 3)
    assert point_cloud_src.size(-1) == 3
    assert point_cloud_tgt.ndimension() == 3  # (B, N, 3)
    assert point_cloud_tgt.size(-1) == 3

    # [B, N, N, 3]
    distance = point_cloud_src[:, :, None, :] - point_cloud_tgt[:, None, :, :]
    # [B, N, N]
```

```python
    distance = torch.sum(distance**2, dim=-1)

    # [B, N]
    min_xy, _ = torch.min(distance, dim=-1)
    min_yx, _ = torch.min(distance.transpose(1, 2), dim=-1)

    # [B]
    loss_xy = min_xy.mean(dim=1)
    loss_yx = min_yx.mean(dim=1)

    return (loss_xy + loss_yx).mean()
```

Model

SingleViewto3D

> An Encoder-Decoder architecture.
>
> Encoder uses ResNet series.
>
> The code I changed:
>
> 1. Freeze the BatchNorm2d layers
>   While using ResNet50 as encoder, I found the batch normalization will make the performance bad.
>   Batch Normalization will be determined by the batch size.
>   If the batch size is very small (e.g. 16, 8...), it will perform not well.
> 2. Build the model automatically.
>   I find it is determined by BasicBlock or BottleBlock.
>   Refer to here.

```python
class SingleViewto3D(nn.Module):
    def __init__(self, cfg):
        super().__init__()
        self.dtype = cfg.dtype
        vision_model: torch.nn.Module = torchvision_resnet.__dict__[cfg.arch](
            pretrained=True
        )
        self.encoder = torch.nn.Sequential(*(list(vision_model.children())[:-1]))
        for module in self.encoder.modules():
            if isinstance(module, nn.BatchNorm2d):
                module.requires_grad_(False)

        latent_size = 512
        for module in vision_model.modules():
            if isinstance(module, torchvision_resnet.BasicBlock):
                latent_size *= torchvision_resnet.BasicBlock.expansion
                break
            elif isinstance(module, torchvision_resnet.Bottleneck):
                latent_size *= torchvision_resnet.Bottleneck.expansion
                break

        # define decoder
        if cfg.dtype == "voxel":
            self.decoder = VoxelDecoder(cfg.n_points, latent_size)
```

```python
        elif cfg.dtype == "point":
            self.decoder = PointDecoder(cfg.n_points, latent_size)

        self.normalize = Normalize(
            mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]
        )

    def forward(self, images: torch.Tensor):
        images = self.normalize(images)
        encoded_feat = self.encoder(images)
        encoded_feat = torch.flatten(encoded_feat, 1)
        pred = logits = self.decoder(encoded_feat)
        if self.dtype == "voxel":
            pred = torch.sigmoid(logits)
        return logits, pred
```

PointDecoder

> The code I changed:
>
> 1. Build the layers automatically.
> 2. Add Group Normalization to let the model coverage more easily.

```python
class PointDecoder(nn.Module):
    def __init__(self, num_points: int, latent_size: int = 512):
        super().__init__()
        self.num_points = num_points
        out_features = self.num_points * 3

        layers = []
        scale = 2
        max_scale = out_features // latent_size
        prev_size = latent_size
        while scale < max_scale:
            next_size = latent_size * scale
            layers.extend(
                [
                    nn.Linear(prev_size, next_size),
                    nn.GroupNorm(32, num_channels=next_size),
                ]
            )
            prev_size = next_size
            scale *= 2

        layers.append(nn.Linear(prev_size, out_features))

        self.layers = nn.ModuleList(layers)
        self.th = nn.Tanh()

    def forward(self, x: torch.Tensor):
        for layer in self.layers[:-1]:
            x = F.relu(layer(x))

        x = self.layers[-1](x)
        x = self.th(x)
```

```
        x = x.view(-1, self.num_points, 3)
        return x
```

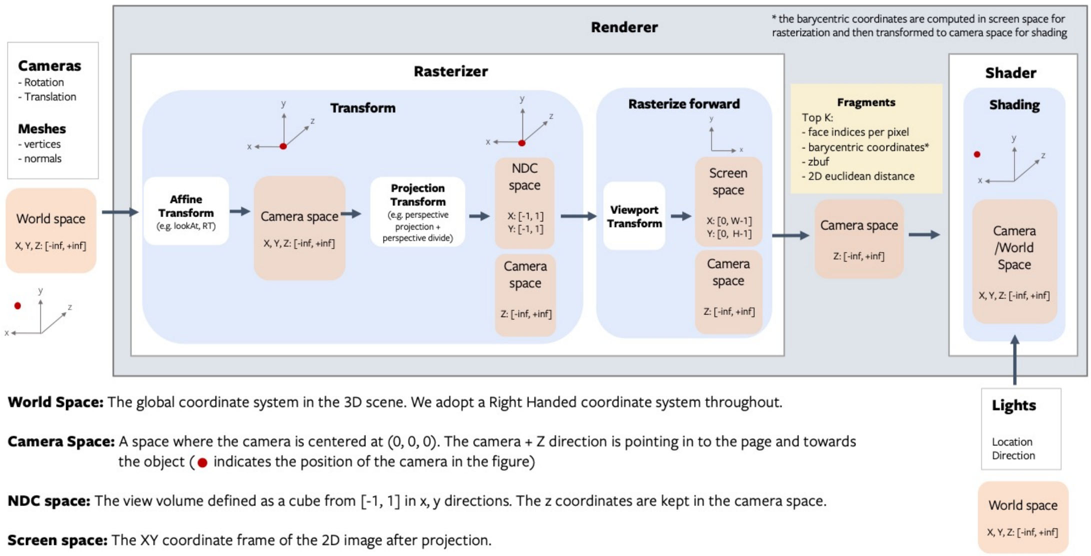
VoxelDecoder

> The code I changed:
>
> 1. Remove Tanh activation layer.
>   Because of binary format of voxels, the decoder predicts multiple binary score.
>   Tanh is used for predicting (-1, 1) values, such as coordinates.
>   So, I change to use sigmoid with binary entropy loss function.
> 2. Add Group Normalization to let the model coverage more easily.

```
class VoxelDecoder(nn.Module):
    def __init__(self, num_points: int, latent_size: int = 512):
        super().__init__()
        self.num_points = num_points
        self.fc0 = nn.Linear(latent_size, latent_size * 2)
        self.gn0 = nn.GroupNorm(32, num_channels=latent_size * 2)
        self.fc1 = nn.Linear(latent_size * 2, latent_size * 4)
        self.gn1 = nn.GroupNorm(32, num_channels=latent_size * 4)

        self.fc5 = nn.Linear(latent_size * 4, self.num_points**3)

    def forward(self, x: torch.Tensor):
        x = self.fc0(x)
        x = self.gn0(x)
        x = F.relu(x)
        x = self.fc1(x)
        x = self.gn1(x)
        x = F.relu(x)

        x = self.fc5(x)
        x = x.view(-1, self.num_points, self.num_points, self.num_points)
        return x
```

Visualization

> Refer to the script scene.py in notebooks folder.
>
> Use pytorch3d.renderer to visualize the point clouds and voxels.
>
> Later, in eval part, I will explain how to convert binary format of voxels to cubes.
>
> Rendering flow ([renderer_getting_started · PyTorch3D]())




```python
class VoxelScene:
    def __init__(self, device: torch.device):
        self.device = device

    def set_cam(self, dist=1.0, elev=0.0, azim=0.0):
        """
        Initialize a camera.
        With world coordinates +Y up, +X left and +Z in.
        see full api in
https://pytorch3d.readthedocs.io/en/latest/modules/renderer/cameras.html#pytorch3d.renderer.cameras.look_at_view_transform
        """
        R, T = look_at_view_transform(dist, elev, azim)
        self.cameras = FoVPerspectiveCameras(device=self.device, R=R, T=T)
        return self

    def set_light(self, location=[[0.0, 0.0, 0.0]]):
        """
        see full api in
https://pytorch3d.readthedocs.io/en/latest/modules/renderer/lighting.html#pytorch3d.renderer.lighting.PointLights
        """
        self.lights = PointLights(location=location, device=self.device)
        return self

    def set_rasterizer(self, image_size=512):
        self.raster_settings = RasterizationSettings(
            image_size=image_size,
            blur_radius=1e-5,
            faces_per_pixel=150,
            bin_size=0,
            cull_backfaces=True,
            # max_faces_per_bin=10,
        )
        """
```

```
        see full api in
https://pytorch3d.readthedocs.io/en/latest/modules/renderer/rasterizer.html#pytor
ch3d.renderer.mesh.rasterizer.RasterizationSettings
        """
        return self

    def set_renderer(self):
        """
        see full api in
https://github.com/facebookresearch/pytorch3d/blob/2c64635daa2aa728f35ed4abe41c69
42ae8c0d8b/pytorch3d/renderer/mesh/renderer.py#L32
        """

        self.renderer = MeshRenderer(
            rasterizer=MeshRasterizer(
                cameras=self.cameras, raster_settings=self.raster_settings
            ),
            shader=SoftGouraudShader(
                device=self.device, cameras=self.cameras, lights=self.lights
            ),
        )

        return self


class PointScene:
    def __init__(self, device: torch.device):
        self.device = device

    def set_cam(self, dist=1.0, elev=0.0, azim=0.0):
        """
        Initialize a camera.
        With world coordinates +Y up, +X left and +Z in.
        see full api in
https://pytorch3d.readthedocs.io/en/latest/modules/renderer/cameras.html#pytorch3
d.renderer.cameras.look_at_view_transform
        """
        R, T = look_at_view_transform(dist, elev, azim)
        self.cameras = FoVPerspectiveCameras(device=self.device, R=R, T=T)
        return self

    def set_rasterizer(self, image_size=512):
        self.raster_settings = PointsRasterizationSettings(
            image_size=image_size,
            radius=1e-2,
            points_per_pixel=120,
            bin_size=0,
            # max_points_per_bin=10,
        )
        """
        see full api in
https://pytorch3d.readthedocs.io/en/latest/modules/renderer/rasterizer.html#pytor
ch3d.renderer.mesh.rasterizer.RasterizationSettings
        """
        return self
```

```
    def set_renderer(self):
        """
        see full api in
https://github.com/facebookresearch/pytorch3d/blob/2c64635daa2aa728f35ed4abe41c69
42ae8c0d8b/pytorch3d/renderer/mesh/renderer.py#L32
        """

        self.renderer = PointsRenderer(
            rasterizer=PointsRasterizer(
                cameras=self.cameras, raster_settings=self.raster_settings
            ),
            compositor=NormWeightedCompositor(background_color=[1.0, 1.0, 1.0]),
        )

        return self
```

Train

> The code I changed:
>
> 1. Change Adam to AdamW
> 2. Visualize loss history
> 3. Choose GPU device from config
> 4. Shuffle the data for each epoch

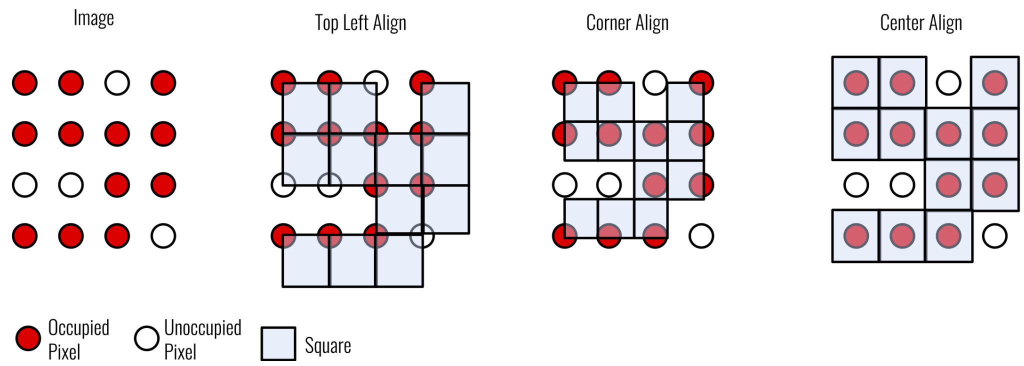
```
def calculate_loss(predictions, ground_truth, cfg):
    if cfg.dtype == "voxel":
        loss = losses.voxel_loss(predictions, ground_truth)
    elif cfg.dtype == "point":
        loss = losses.chamfer_loss(predictions, ground_truth)
    return loss


@hydra.main(config_path="configs/", config_name="config.yaml")
def train_model(cfg: DictConfig):
    log.info(f"Device: {cfg.device}")
    device = torch.device(cfg.device)

    log.info(cfg.data_dir)
    shapenetdb = ShapeNetDB(cfg.data_dir, cfg.dtype)

    loader = torch.utils.data.DataLoader(
        shapenetdb,
        batch_size=cfg.batch_size,
        num_workers=cfg.num_workers,
        pin_memory=True,
        drop_last=False,
        shuffle=True,
    )
    train_loader = iter(loader)

    if cfg.dtype == "voxel":
        cfg.n_points = shapenetdb[0][1].shape[1]
```

```
    model = SingleViewto3D(cfg)
    model.cuda(device)
    model.train()

    # ============ preparing optimizer ... ============
    optimizer = torch.optim.AdamW(
        model.parameters(), lr=cfg.lr, weight_decay=cfg.weight_decay
    )  # to use with ViTs
    start_iter = 0
    start_time = time.time()

    if cfg.load_checkpoint:
        checkpoint = torch.load(f"{cfg.base_dir}/checkpoint_{cfg.dtype}.pth")
        model.load_state_dict(checkpoint["model_state_dict"])
        optimizer.load_state_dict(checkpoint["optimizer_state_dict"])
        start_iter = checkpoint["step"]
        log.info(f"Succesfully loaded iter {start_iter}")

    log.info("Starting training !")
    best_loss = sys.float_info.max
    loss_history = []
    for step in range(start_iter, cfg.max_iter):
        iter_start_time = time.time()

        if step % len(train_loader) == 0:  # restart after one epoch
            train_loader = iter(loader)

        read_start_time = time.time()

        images_gt, ground_truth_3d, _ = next(train_loader)
        images_gt, ground_truth_3d = images_gt.cuda(device),
ground_truth_3d.cuda(
            device
        )

        read_time = time.time() - read_start_time

        prediction_logits: torch.Tensor
        prediction_logits, _ = model(images_gt)

        loss = calculate_loss(prediction_logits, ground_truth_3d, cfg)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_time = time.time() - start_time
        iter_time = time.time() - iter_start_time

        loss_vis = loss.detach().cpu().item()

        if loss_vis < best_loss:
            best_loss = loss_vis
            torch.save(
                {
                    "step": step,
```

```python
                    "model_state_dict": model.state_dict(),
                    "optimizer_state_dict": optimizer.state_dict(),
                },
                f"{cfg.base_dir}/checkpoint_{cfg.dtype}.pth",
            )

        # if (step % cfg.save_freq) == 0:
        #     torch.save(
        #         {
        #             "step": step,
        #             "model_state_dict": model.state_dict(),
        #             "optimizer_state_dict": optimizer.state_dict(),
        #         },
        #         f"{cfg.base_dir}/checkpoint_{cfg.dtype}.pth",
        #     )

        log.info(
            "[%4d/%4d]; ttime: %.0f (%.2f, %.2f); loss: %.5f"
            % (step, cfg.max_iter, total_time, read_time, iter_time, loss_vis)
        )

        loss_history.append(loss_vis)

    log.info("Done!")

    log.info("Best loss: %.5f" % (best_loss))

    fig = plt.figure()
    axe = fig.add_subplot()
    axe.plot(loss_history)
    axe.set_title("Training Loss")
    axe.set_xlabel("Iteration")
    axe.set_ylabel("Loss")
    fig.savefig(f"loss_{cfg.dtype}.jpg")
    plt.close(fig)
```

Eval

> The code I changed:
>
> 1. Choose GPU device from config
> 2. Implement visualization functions
>
> Point cloud visualization `plot_points` function:
>
> 1. Convert points to pytoch3d.structures.Pointclouds
> 2. Use PointsRenderer to visualize gt and prediction.
>
> Voxel visualization (`plot_voxels` function):
>
> 1. Cubify the voxels into Meshes ([cubify]() function is provided by pytorch3d.ops)
>
>   I use center align.



2. Add color textures to meshs

3. Use MeshRenderer to visualize gt and prediction.

```
def calculate_loss(predictions, ground_truth, cfg):
    if cfg.dtype == "voxel":
        loss = losses.voxel_loss(predictions, ground_truth)
    elif cfg.dtype == "point":
        loss = losses.chamfer_loss(predictions, ground_truth)
    return loss


def plot_points(predictions: torch.Tensor) -> torch.Tensor:
    normals = estimate_pointcloud_normals(predictions)
    point_clouds = Pointclouds(
        points=predictions,
        normals=normals,
        features=torch.full_like(predictions, 0.5, device=predictions.device),
    )

    scene = PointScene(predictions.device)
    scene.set_cam(1.8, 45.0, 45.0)
    scene.set_rasterizer(image_size=256)
    scene.set_renderer()
    images = scene.renderer(point_clouds)
    return images


def plot_voxels(predictions: torch.Tensor):
    meshes = cubify(predictions, thresh=0.5, align="center")

    verts_list = meshes.verts_packed()
    verts_rgb = torch.ones(1, verts_list.shape[0], 3, device=predictions.device)
    meshes.textures = TexturesVertex(verts_features=verts_rgb)

    scene = VoxelScene(predictions.device)
    scene.set_cam(2.5, 45.0, 45.0)
    scene.set_light(location=[[0.0, 0.0, 0.0]])
    scene.set_rasterizer(image_size=256)
    scene.set_renderer()
    images = scene.renderer(meshes)
    return images


@torch.no_grad()
```

```
@hydra.main(config_path="configs/", config_name="config.yaml")
def evaluate_model(cfg: DictConfig):
    device = torch.device(cfg.device)

    shapenetdb = ShapeNetDB(cfg.data_dir, cfg.dtype, cfg.n_points)

    loader = torch.utils.data.DataLoader(
        shapenetdb,
        batch_size=cfg.batch_size,
        num_workers=cfg.num_workers,
        pin_memory=True,
        drop_last=True,
        shuffle=False,
    )
    eval_loader = iter(loader)

    if cfg.dtype == "voxel":
        cfg.n_points = shapenetdb[0][1].shape[1]

    model = SingleViewto3D(cfg)
    model.cuda(device)
    model.eval()

    start_iter = 0
    start_time = time.time()

    avg_loss = []

    if cfg.load_eval_checkpoint:
        checkpoint = torch.load(f"{cfg.base_dir}/checkpoint_{cfg.dtype}.pth")
        model.load_state_dict(checkpoint["model_state_dict"])
        log.info(f"Succesfully loaded iter {start_iter}")

    vis_dir = os.path.join(cfg.base_dir, "vis")
    os.makedirs(vis_dir, exist_ok=True)

    log.info("Starting evaluating !")
    max_iter = len(eval_loader)
    for step in range(start_iter, max_iter):
        iter_start_time = time.time()

        read_start_time = time.time()

        images_gt, ground_truth_3d, _ = next(eval_loader)
        images_gt, ground_truth_3d = images_gt.cuda(device),
ground_truth_3d.cuda(
            device
        )

        read_time = time.time() - read_start_time

        prediction_logits: torch.Tensor
        prediction_3d: torch.Tensor
        prediction_logits, prediction_3d = model(images_gt)
        torch.save(prediction_3d.cpu(), f"{cfg.base_dir}/pre_point_cloud.pt")
```

```
        loss = calculate_loss(prediction_logits, ground_truth_3d,
cfg).cpu().item()

        if (step % cfg.vis_freq) == 0:
            # visualization block
            if cfg.dtype == "point":
                gt_images = plot_points(ground_truth_3d)
                images = plot_points(prediction_3d)
            elif cfg.dtype == "voxel":
                gt_images = plot_voxels(ground_truth_3d)
                images = plot_voxels(prediction_3d)

            rgb_images = images_gt.permute(0, 2, 3, 1).cpu().numpy()
            gt_images = gt_images.cpu().numpy()
            images = images.cpu().numpy()

            f = plt.figure()
            for i in range(images.shape[0]):
                rgb_image = rgb_images[i]
                gt_image = gt_images[i]
                image = images[i]

                axeses = f.subplots(1, 3, sharey=True)
                for axes in axeses:
                    axes.xaxis.set_visible(False)
                    axes.yaxis.set_visible(False)

                ax1, ax2, ax3 = axeses
                ax1.set_title("GT Image")
                ax1.imshow(rgb_image)

                ax2.set_title("GT 3D")
                ax2.imshow(gt_image)

                ax3.set_title("Prediction 3D")
                ax3.imshow(image)

                file_name = os.path.join(vis_dir, f"{step}_{cfg.dtype}_{i}.png")
                f.savefig(file_name)
                f.clf()
            plt.close(f)

        total_time = time.time() - start_time
        iter_time = time.time() - iter_start_time

        avg_loss.append(loss)

        log.info(
            "[%4d/%4d]; ttime: %.0f (%.2f, %.2f); eva_loss: %.3f"
            % (
                step,
                max_iter,
                total_time,
                read_time,
                iter_time,
                torch.tensor(avg_loss).mean(),
```

```
            )
        )

    log.info("Done!")
```

Visualization and analysis of your experiment result

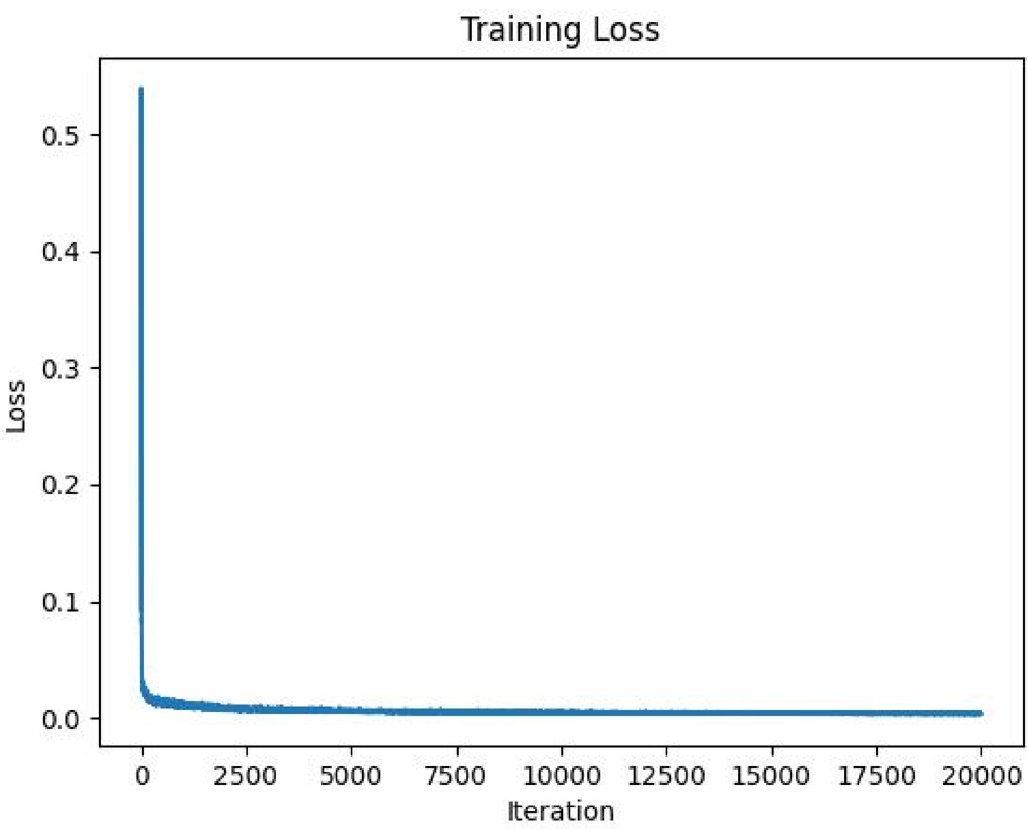
Point cloud

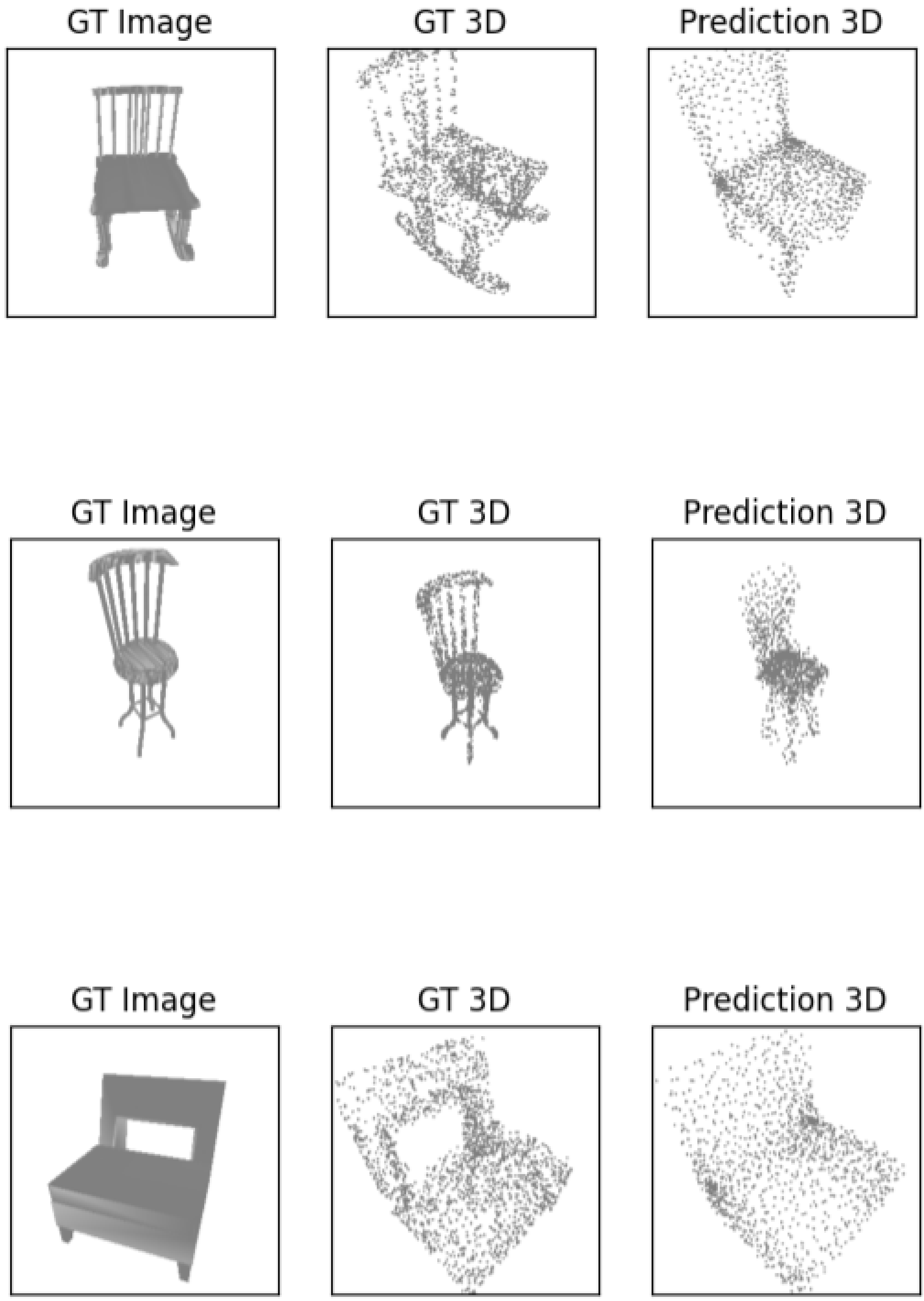
Settings

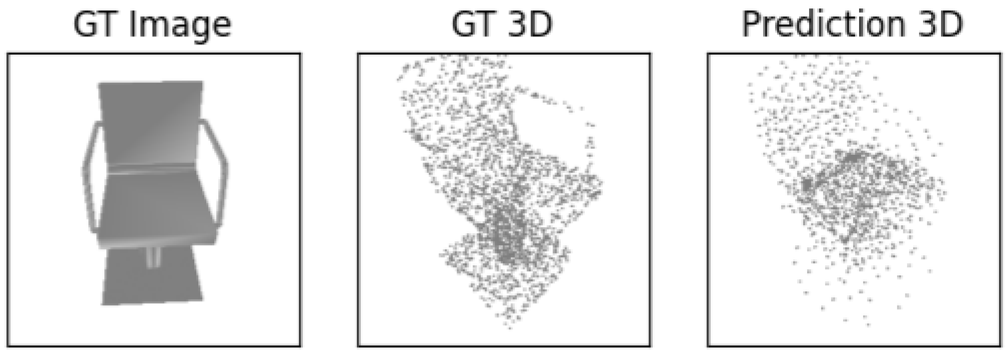
- learning rate: 0.001
- weight decay: 0.01
- max iterations: 20000
- batch size: 32(ResNet18, Resnet34), 16(ResNet50, ResNet101)
- num workers: 4

ResNet18

> Best Loss: 0.00271
>
> Although the loss is very low, the points spread every where.
>
> This also explains why chamfer loss is not the best option.
>
> Chamfer loss is using the nearest point to calculate. It does not filter out the selected points.
>
> So, some points may be constrained by loss function many times.

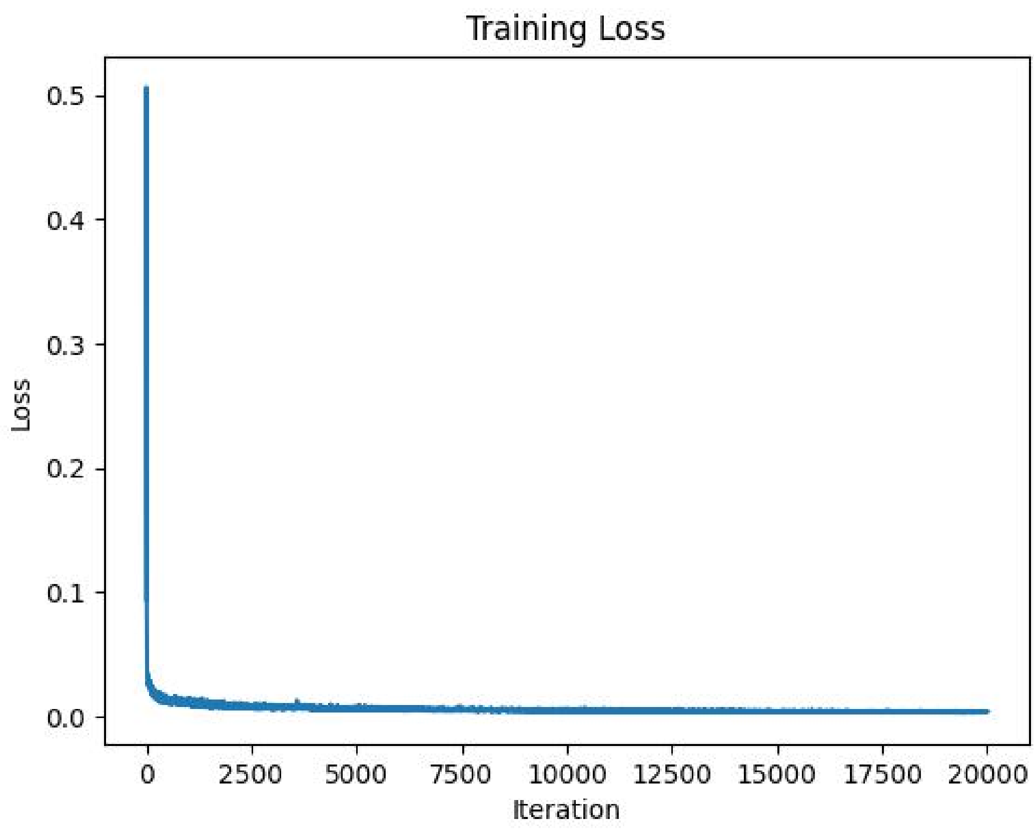


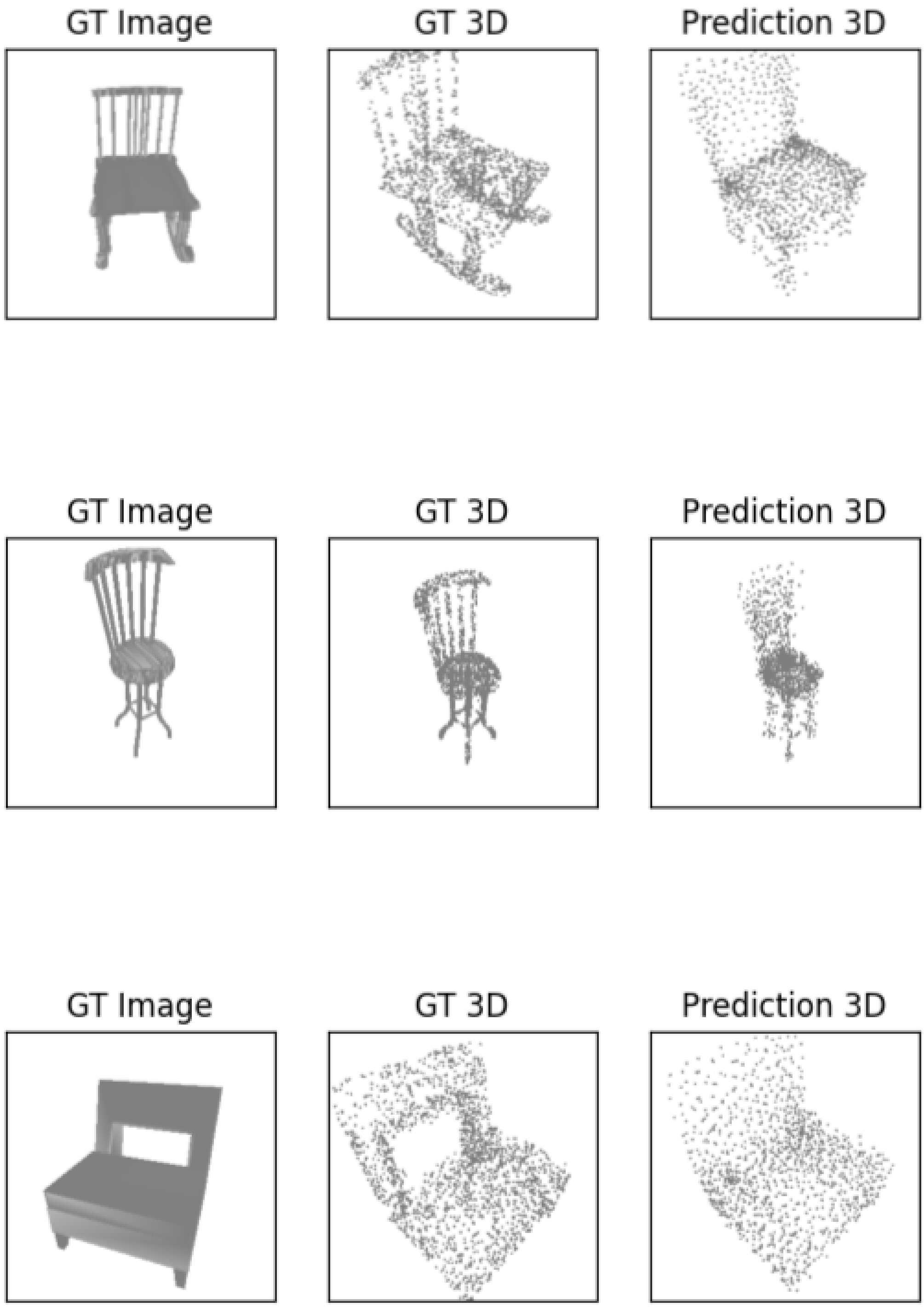

GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D



Resnet34

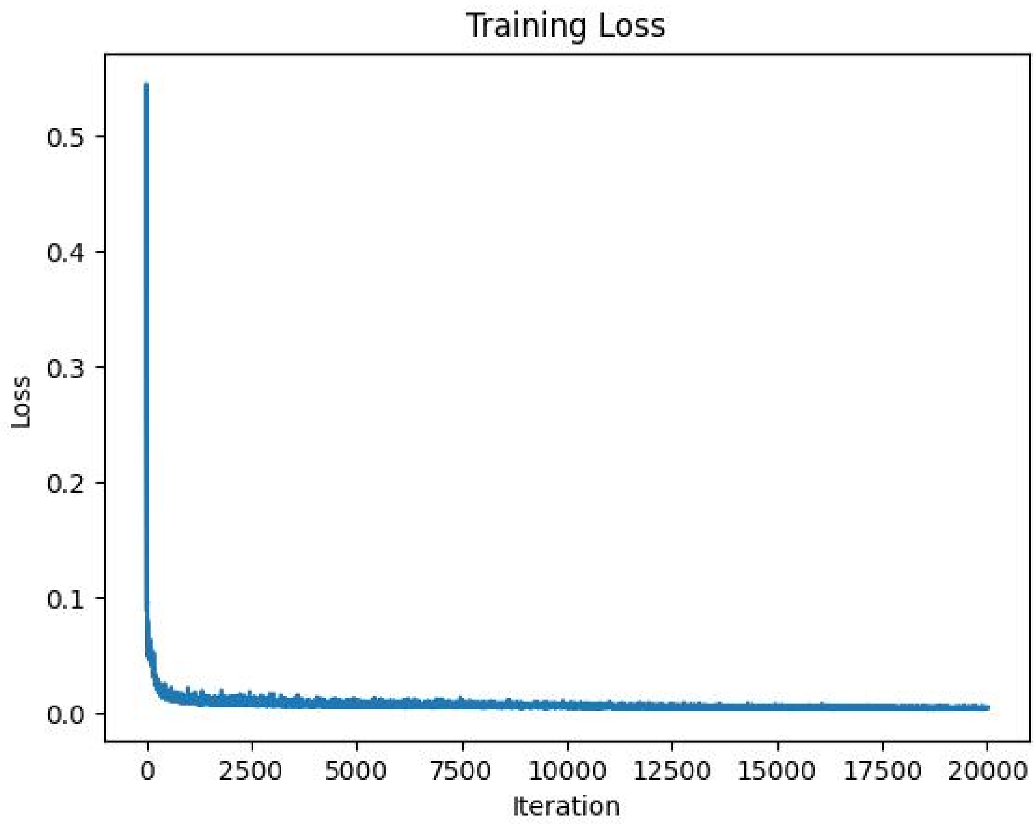
> Best Loss: 0.00253
>
> Same problem.
>
> Although the loss is very low, the points spread every where.

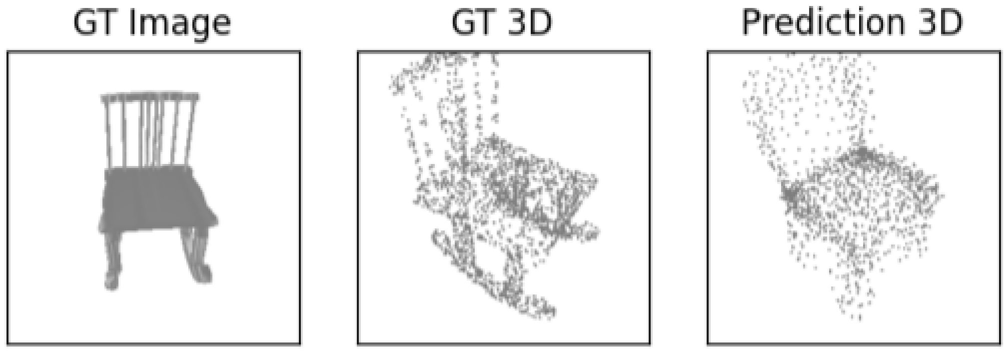


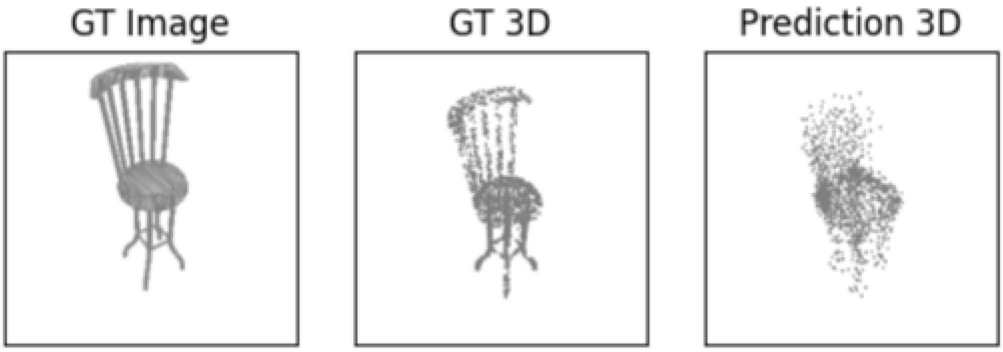

GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D

ResNet50

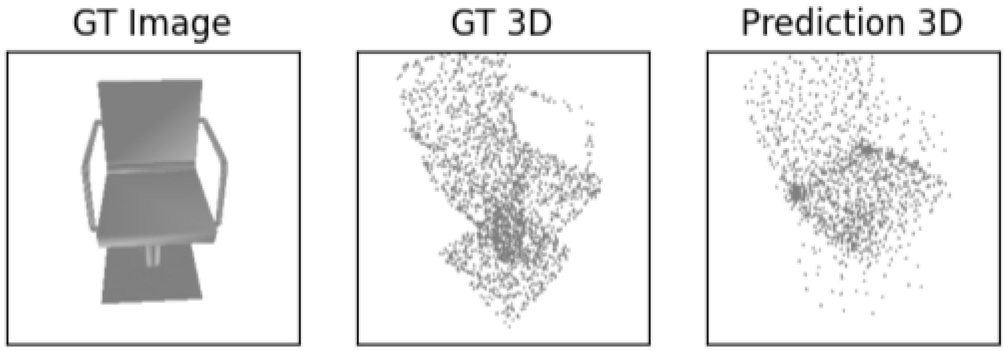
> Best Loss: 0.00276
>
> Same problem.
>
> Although the loss is very low, the points spread every where.
>
> From these results, I thinks it coverage.




GT Image
GT 3D
Prediction 3D


GT Image
GT 3D
Prediction 3D


GT Image
GT 3D
Prediction 3D



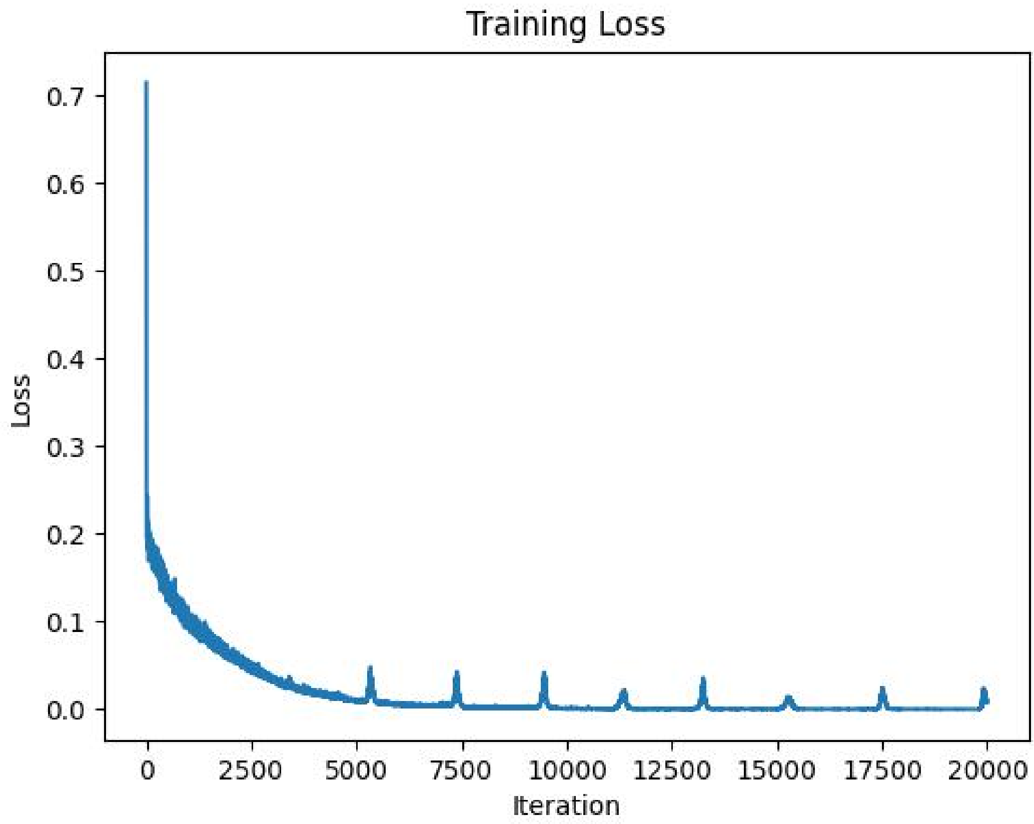
Voxel

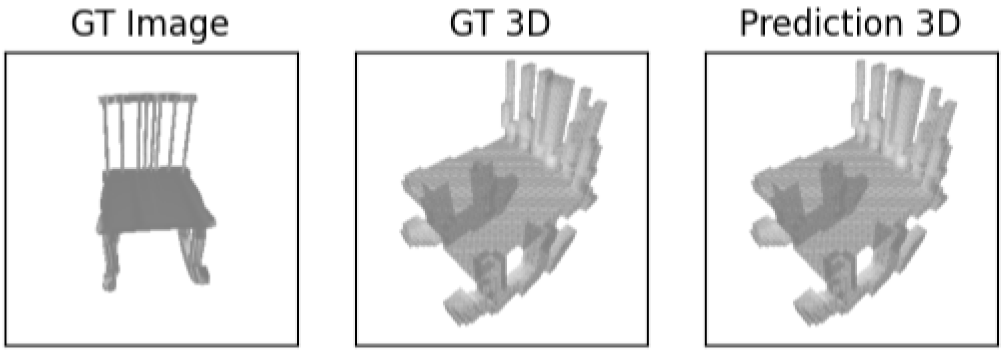
Settings

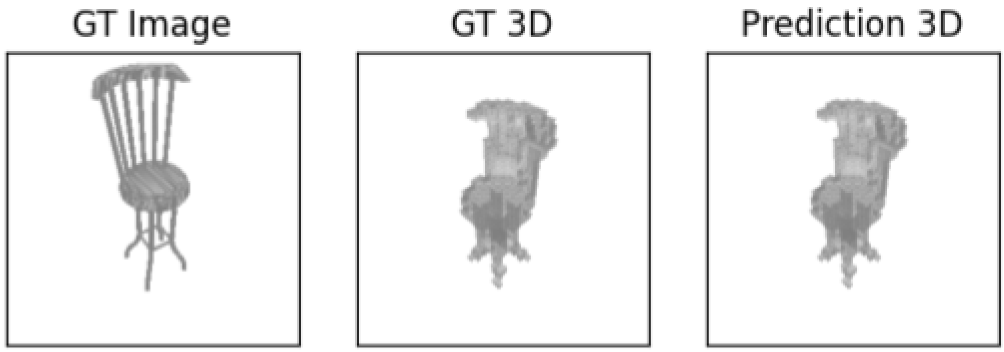
- learning rate: 0.001
- weight decay: 0.01
- max iterations: 20000
- batch size: 256(ResNet18), 32(ResNet50)
- num workers: 4

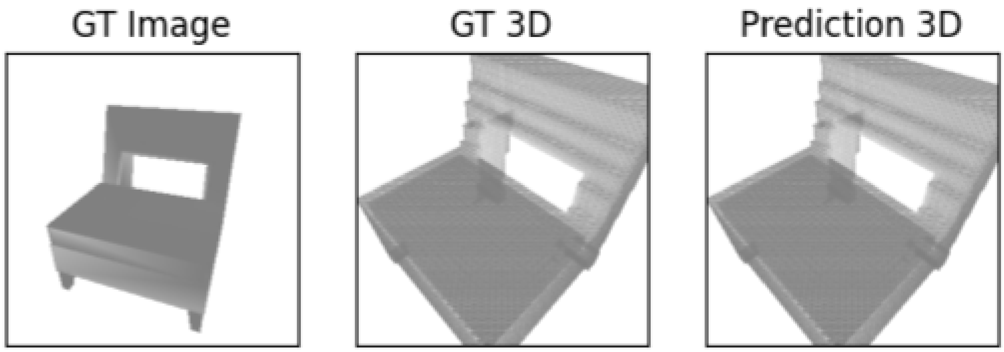
ResNet18

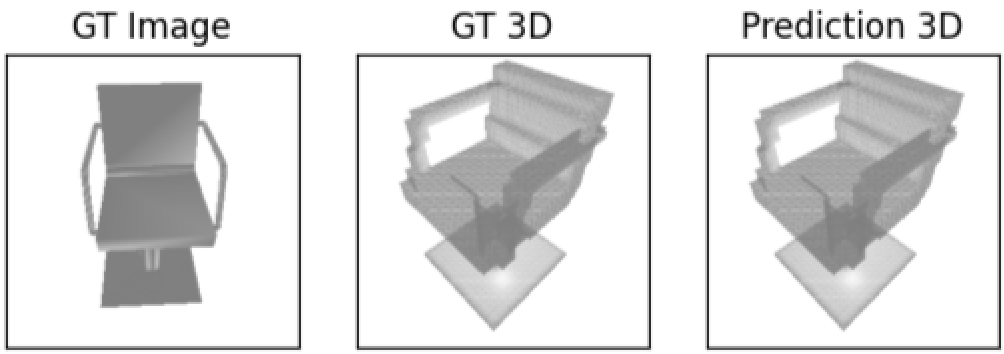
> Best Loss: 0.00007
>
> The model overfits(maybe) perfectly.




GT Image
GT 3D
Prediction 3D

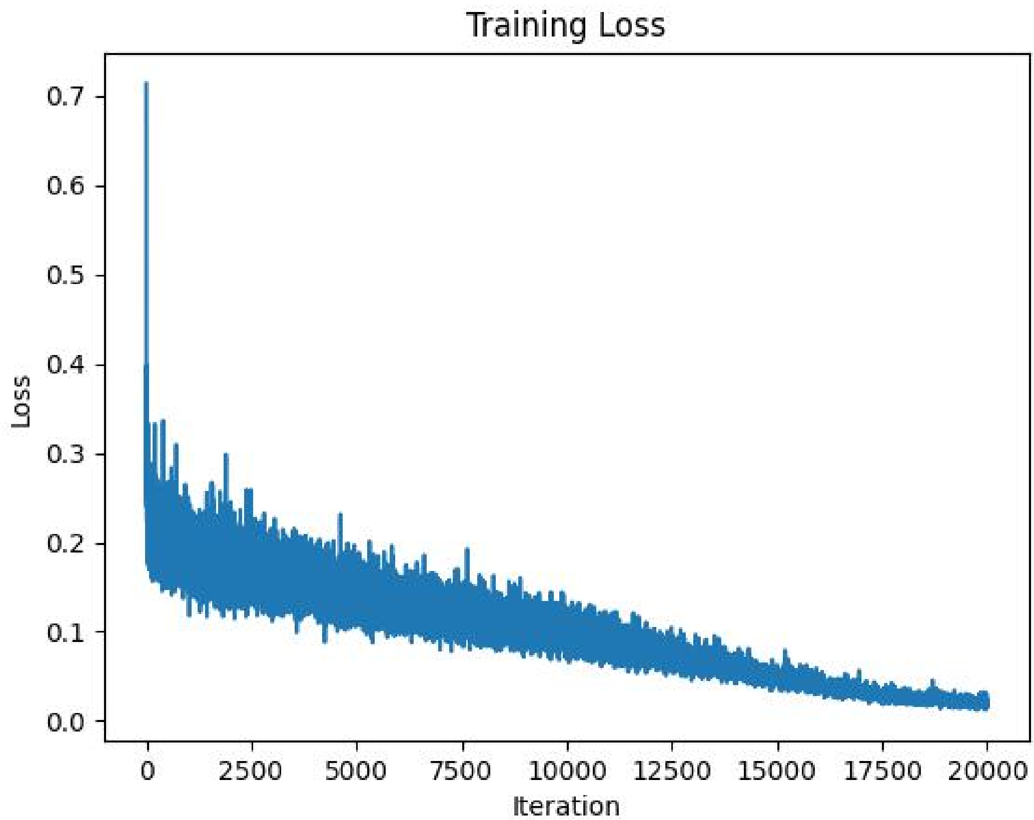

GT Image
GT 3D
Prediction 3D

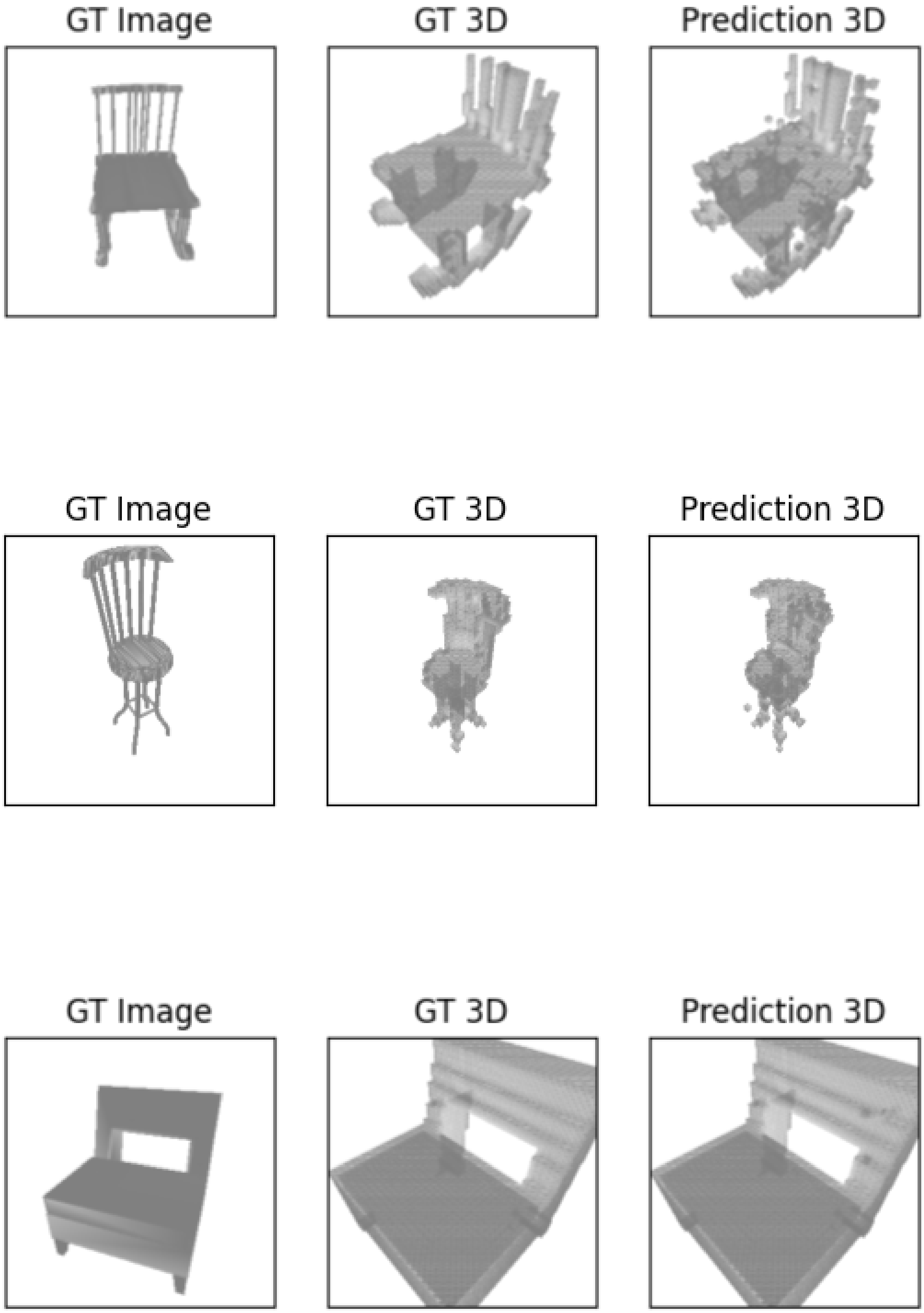

GT Image
GT 3D
Prediction 3D



ResNet50

> Best Loss: 0.01257
>
> Due to not enough GPU memory space, the batch size is decreased.
>
> So, the model needs more iterations to coverage.
>
> But I think it will be like previous one overfitting perfectly 👌 .




GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D
GT Image
GT 3D
Prediction 3D