Diffusion Model

April 15, 2024

[ ]:
```python
import torchvision.transforms as transforms
import torch.nn as nn
import torchvision
import math
import matplotlib.pyplot as plt
import torch
import urllib
import numpy as np
import PIL
```

[ ]:
```python
device = torch.device("cuda:1")
```

[ ]:
```python
def get_sample_image()-> PIL.Image.Image:
    url = 'https://encrypted-tbn0.gstatic.com/images?q=tbn:
↪ANd9GcTZmJy3aSZ1Ix573d2MlJXQowLCLQyIUsPdniOJ7rBsgG4XJb04g9ZFA9MhxYvckeKkVmo&usqp=CAU'
    filename = 'racoon.jpg'
    urllib.request.urlretrieve(url, filename)
    return PIL.Image.open(filename)
```

[ ]:
```python
def plot_noise_distribution(noise, predicted_noise):
    plt.hist(noise.cpu().numpy().flatten(), density = True, alpha = 0.8, label␣
↪= "ground truth noise")
    plt.hist(predicted_noise.cpu().numpy().flatten(), density = True, alpha = 0.
↪8, label = "predicted noise")
    plt.legend()
    plt.show()
```

[ ]:
```python
def plot_noise_prediction(noise, predicted_noise):
    plt.figure(figsize=(15,15))
    f, ax = plt.subplots(1, 2, figsize = (5,5))
    ax[0].imshow(reverse_transform(noise))
    ax[0].set_title(f"ground truth noise", fontsize = 10)
    ax[1].imshow(reverse_transform(predicted_noise))
    ax[1].set_title(f"predicted noise", fontsize = 10)
    plt.show()
```

```
[ ]: class DiffusionModel:
    def __init__(self, start_schedule=0.0001, end_schedule=0.02, timesteps =␣
 ↪300):
        self.start_schedule = start_schedule
        self.end_schedule = end_schedule
        self.timesteps = timesteps

        """
        if
            betas = [0.1, 0.2, 0.3, ...]
        then
            alphas = [0.9, 0.8, 0.7, ...]
            alphas_cumprod = [0.9, 0.9 * 0.8, 0.9 * 0.8, * 0.7, ...]


        """
        self.betas = torch.linspace(start_schedule, end_schedule, timesteps)
        self.alphas = 1 - self.betas
        self.alphas_cumprod = torch.cumprod(self.alphas, axis=0)

    def forward(self, x_0, t, device):
        """
        x_0: (B, C, H, W)
        t: (B,)
        """
        noise = torch.randn_like(x_0)
        sqrt_alphas_cumprod_t = self.get_index_from_list(self.alphas_cumprod.
 ↪sqrt(), t, x_0.shape)
        sqrt_one_minus_alphas_cumprod_t = self.get_index_from_list(torch.sqrt(1.
 ↪ - self.alphas_cumprod), t, x_0.shape)

        mean = sqrt_alphas_cumprod_t.to(device) * x_0.to(device)
        variance = sqrt_one_minus_alphas_cumprod_t.to(device) * noise.to(device)

        return mean + variance, noise.to(device)

    @torch.no_grad()
    def backward(self, x, t, model, **kwargs):
        """
        Calls the model to predict the noise in the image and returns
        the denoised image.
        Applies noise to this image, if we are not in the last step yet.
        """
        betas_t = self.get_index_from_list(self.betas, t, x.shape)
        sqrt_one_minus_alphas_cumprod_t = self.get_index_from_list(torch.sqrt(1.
 ↪ - self.alphas_cumprod), t, x.shape)
```

```
        sqrt_recip_alphas_t = self.get_index_from_list(torch.sqrt(1.0 / self.
↪alphas), t, x.shape)
        mean = sqrt_recip_alphas_t * (x - betas_t * model(x, t, **kwargs) /␣
↪sqrt_one_minus_alphas_cumprod_t)
        posterior_variance_t = betas_t

        if t == 0:
            return mean
        else:
            noise = torch.randn_like(x)
            variance = torch.sqrt(posterior_variance_t) * noise
            return mean + variance

    @staticmethod
    def get_index_from_list(values, t, x_shape):
        batch_size = t.shape[0]
        """
        pick the values from vals
        according to the indices stored in `t`
        """
        result = values.gather(-1, t.cpu())
        """
        if
        x_shape = (5, 3, 64, 64)
            -> len(x_shape) = 4
            -> len(x_shape) - 1 = 3

        and thus we reshape `out` to dims
        (batch_size, 1, 1, 1)

        """
        return result.reshape(batch_size, *((1,) * (len(x_shape) - 1))).to(t.
↪device)
```

[ ]:
```
IMAGE_SHAPE = (32, 32)
```

[ ]:
```
transform = transforms.Compose([
    transforms.Resize(IMAGE_SHAPE), # Resize the input image
    transforms.ToTensor(), # Convert to torch tensor (scales data into [0,1])
    transforms.Lambda(lambda t: (t * 2) - 1), # Scale data between [-1, 1]
])


reverse_transform = transforms.Compose([
    transforms.Lambda(lambda t: (t + 1) / 2), # Scale data between [0,1]
```

```
    transforms.Lambda(lambda t: t.permute(1, 2, 0)), # CHW to HWC
    transforms.Lambda(lambda t: t * 255.), # Scale data between [0.,255.]
    transforms.Lambda(lambda t: t.cpu().numpy().astype(np.uint8)), # Convert␣
↪into an uint8 numpy array
    transforms.ToPILImage(), # Convert to PIL image
])
```

[ ]:

```
pil_image = get_sample_image()
torch_image = transform(pil_image)
```

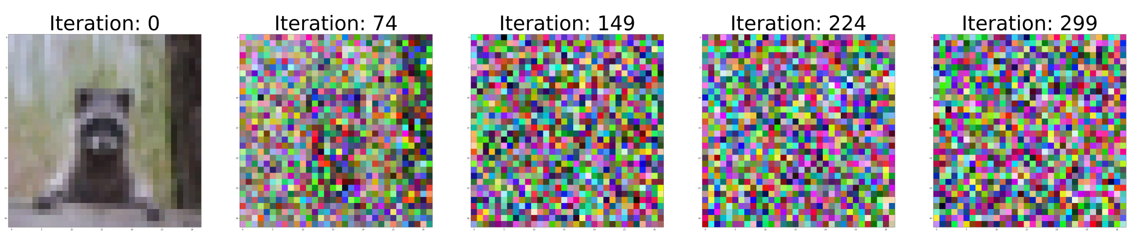
[ ]:

```
diffusion_model = DiffusionModel()
```

[ ]:

```
NO_DISPLAY_IMAGES = 5
torch_image_batch = torch.stack([torch_image] * NO_DISPLAY_IMAGES)
t = torch.linspace(0, diffusion_model.timesteps - 1, NO_DISPLAY_IMAGES).long()
noisy_image_batch, _ = diffusion_model.forward(torch_image_batch, t, device)

plt.figure(figsize=(15,15))
f, ax = plt.subplots(1, NO_DISPLAY_IMAGES, figsize = (100,100))

for idx, image in enumerate(noisy_image_batch):
    ax[idx].imshow(reverse_transform(image))
    ax[idx].set_title(f"Iteration: {t[idx].item()}", fontsize = 100)
plt.show()
```

```
<Figure size 1500x1500 with 0 Axes>
```



[ ]:

```
class SinusoidalPositionEmbeddings(nn.Module):
    def __init__(self, dim):
        super().__init__()
        self.dim = dim

    def forward(self, time):
        device = time.device
        half_dim = self.dim // 2
        embeddings = math.log(10000) / (half_dim - 1)
```

```
        embeddings = torch.exp(torch.arange(half_dim, device=device) *␣
↪-embeddings)
        embeddings = time[:, None] * embeddings[None, :]
        embeddings = torch.cat((embeddings.sin(), embeddings.cos()), dim=-1)
        return embeddings
```

[ ]:
```
class Block(nn.Module):
    def __init__(self, channels_in, channels_out, time_embedding_dims, labels,␣
↪num_filters = 3, downsample=True):
        super().__init__()

        self.time_embedding_dims = time_embedding_dims
        self.time_embedding = SinusoidalPositionEmbeddings(time_embedding_dims)
        self.labels = labels
        if labels:
            self.label_mlp = nn.Linear(1, channels_out)

        self.downsample = downsample

        if downsample:
            self.conv1 = nn.Conv2d(channels_in, channels_out, num_filters,␣
↪padding=1)
            self.final = nn.Conv2d(channels_out, channels_out, 4, 2, 1)
        else:
            self.conv1 = nn.Conv2d(2 * channels_in, channels_out, num_filters,␣
↪padding=1)
            self.final = nn.ConvTranspose2d(channels_out, channels_out, 4, 2, 1)

        self.bnorm1 = nn.BatchNorm2d(channels_out)
        self.bnorm2 = nn.BatchNorm2d(channels_out)

        self.conv2 = nn.Conv2d(channels_out, channels_out, 3, padding=1)
        self.time_mlp = nn.Linear(time_embedding_dims, channels_out)
        self.relu = nn.ReLU()

    def forward(self, x, t, **kwargs):
        o = self.bnorm1(self.relu(self.conv1(x)))
        o_time = self.relu(self.time_mlp(self.time_embedding(t)))
        o = o + o_time[(..., ) + (None, ) * 2]
        if self.labels:
            label = kwargs.get('labels')
            o_label = self.relu(self.label_mlp(label))
            o = o + o_label[(..., ) + (None, ) * 2]

        o = self.bnorm2(self.relu(self.conv2(o)))

        return self.final(o)
```

```
[ ]: class UNet(nn.Module):
        def __init__(self, img_channels = 3, time_embedding_dims = 128, labels =␣
     ↪False, sequence_channels = (64, 128, 256, 512, 1024)):
            super().__init__()
            self.time_embedding_dims = time_embedding_dims
            sequence_channels_rev = reversed(sequence_channels)

            self.downsampling = nn.ModuleList([Block(channels_in, channels_out,␣
     ↪time_embedding_dims, labels) for channels_in, channels_out in␣
     ↪zip(sequence_channels, sequence_channels[1:])])
            self.upsampling = nn.ModuleList([Block(channels_in, channels_out,␣
     ↪time_embedding_dims, labels,downsample=False) for channels_in, channels_out␣
     ↪in zip(sequence_channels[::-1], sequence_channels[::-1][1:])])
            self.conv1 = nn.Conv2d(img_channels, sequence_channels[0], 3, padding=1)
            self.conv2 = nn.Conv2d(sequence_channels[0], img_channels, 1)


        def forward(self, x, t, **kwargs):
            residuals = []
            o = self.conv1(x)
            for ds in self.downsampling:
                o = ds(o, t, **kwargs)
                residuals.append(o)
            for us, res in zip(self.upsampling, reversed(residuals)):
                o = us(torch.cat((o, res), dim=1), t, **kwargs)

            return self.conv2(o)
```

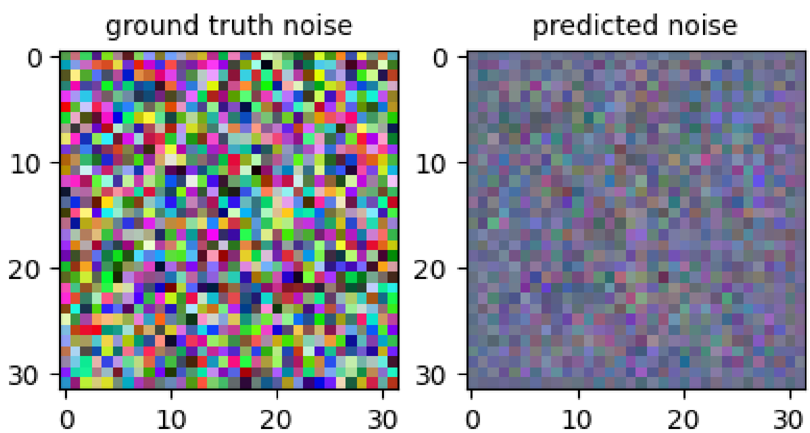
```
[ ]: NO_EPOCHS = 2000
     PRINT_FREQUENCY = 400
     LR = 0.001
     BATCH_SIZE = 128
     VERBOSE = True

     unet = UNet(labels=False)
     unet.to(device)
     optimizer = torch.optim.Adam(unet.parameters(), lr=LR)
```

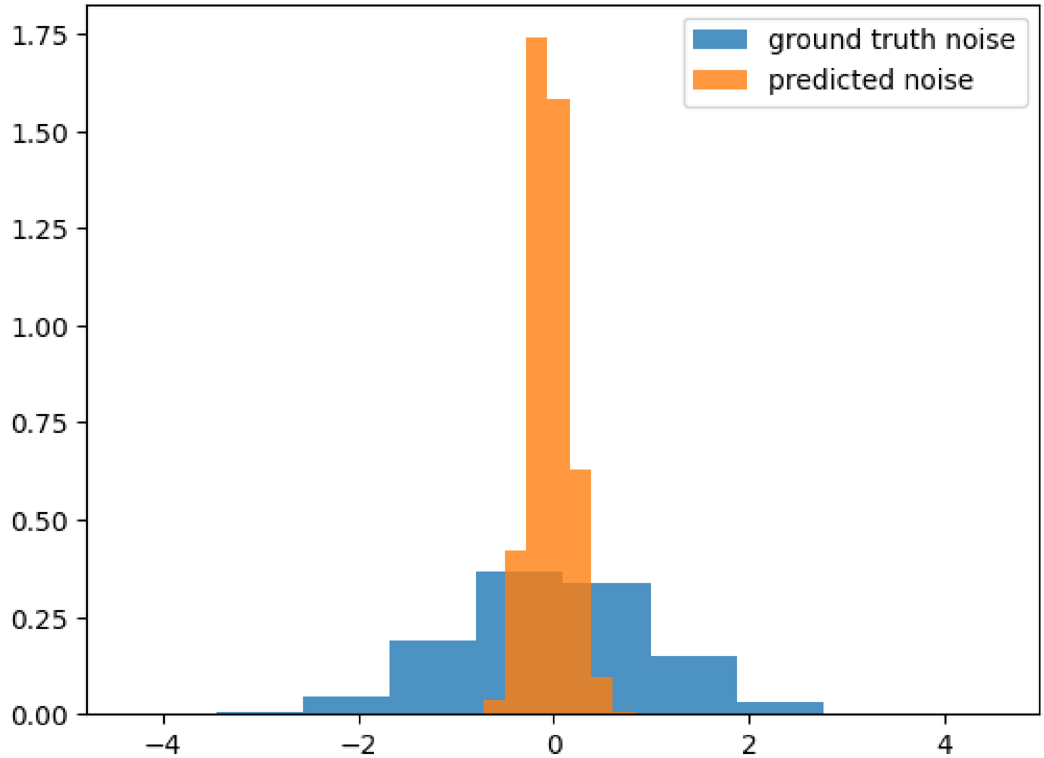
```
[ ]: for epoch in range(NO_EPOCHS):
         mean_epoch_loss = []

         batch = torch.stack([torch_image] * BATCH_SIZE)
         t = torch.randint(0, diffusion_model.timesteps, (BATCH_SIZE,)).long().
     ↪to(device)

         batch_noisy, noise = diffusion_model.forward(batch, t, device)
         predicted_noise = unet(batch_noisy, t)
```

```
    optimizer.zero_grad()
    loss = torch.nn.functional.mse_loss(noise, predicted_noise)
    mean_epoch_loss.append(loss.item())
    loss.backward()
    optimizer.step()

    if epoch % PRINT_FREQUENCY == 0:
        print('---')
        print(f"Epoch: {epoch} | Train Loss {np.mean(mean_epoch_loss)}")
        if VERBOSE:
            with torch.no_grad():
                plot_noise_prediction(noise[0], predicted_noise[0])
                plot_noise_distribution(noise, predicted_noise)
```

```
---
Epoch: 0 | Train Loss 1.0523738861083984
```

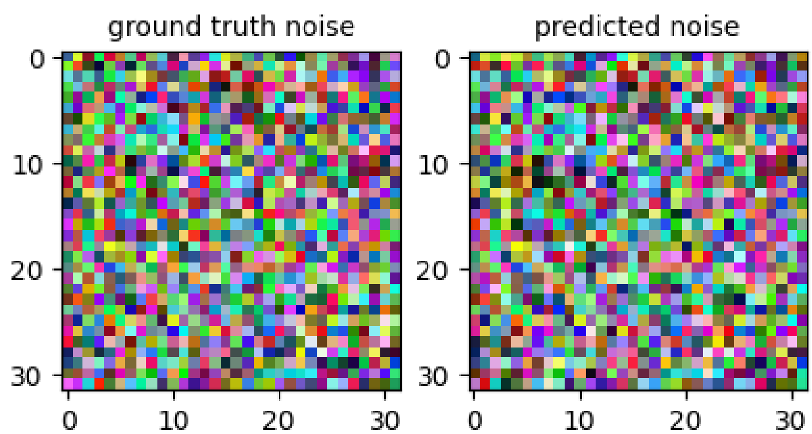
```
<Figure size 1500x1500 with 0 Axes>
```

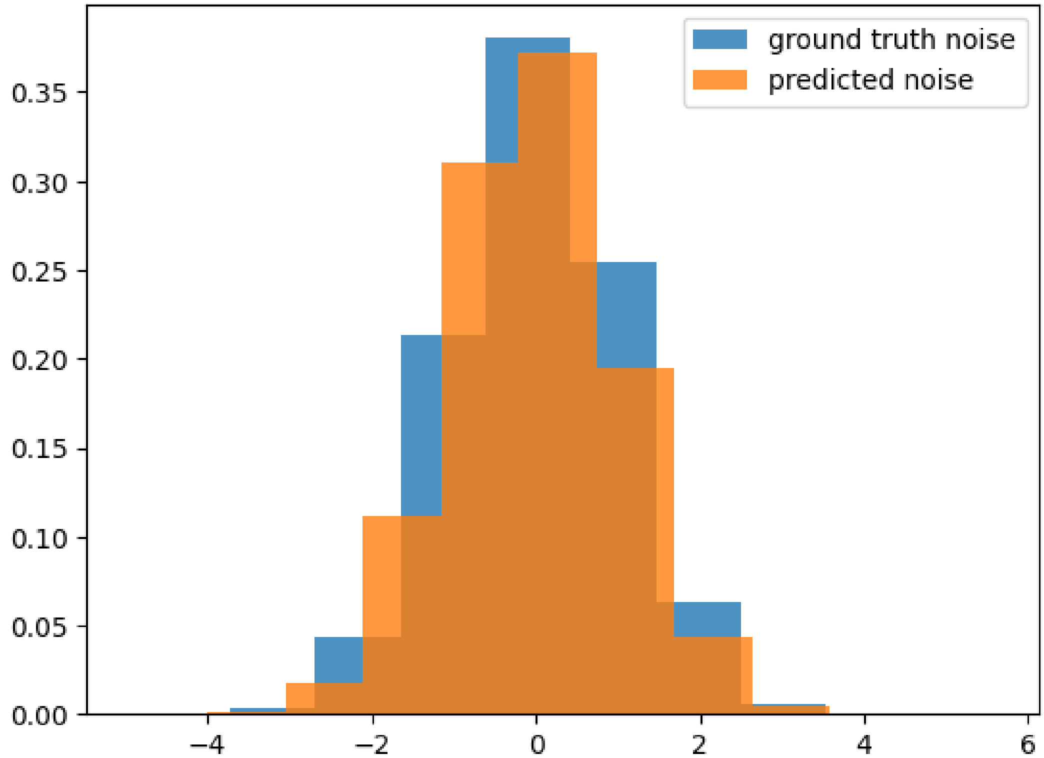





```
---
Epoch: 400 | Train Loss 0.01622544787824154
```

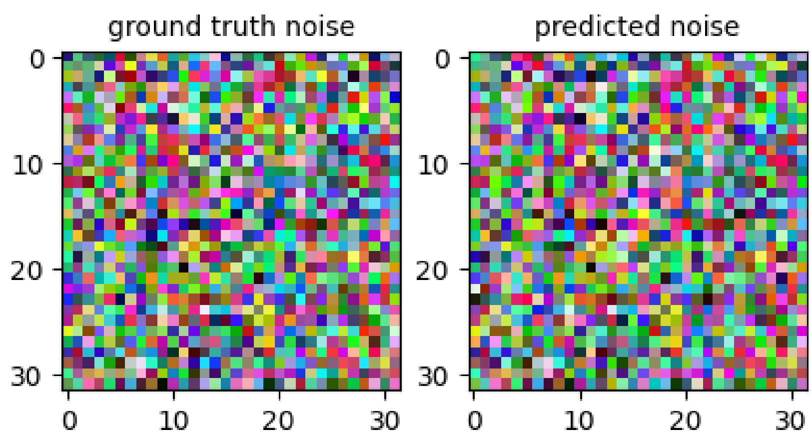
```
<Figure size 1500x1500 with 0 Axes>
```

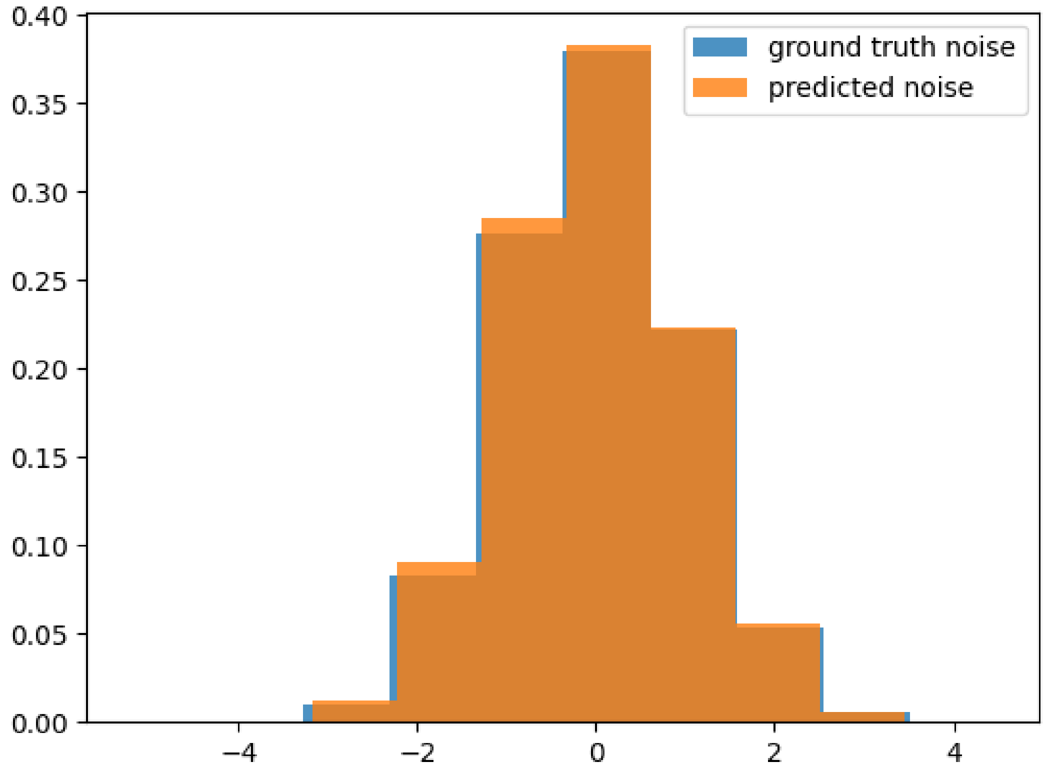




Epoch: 800 | Train Loss 0.007120359688997269

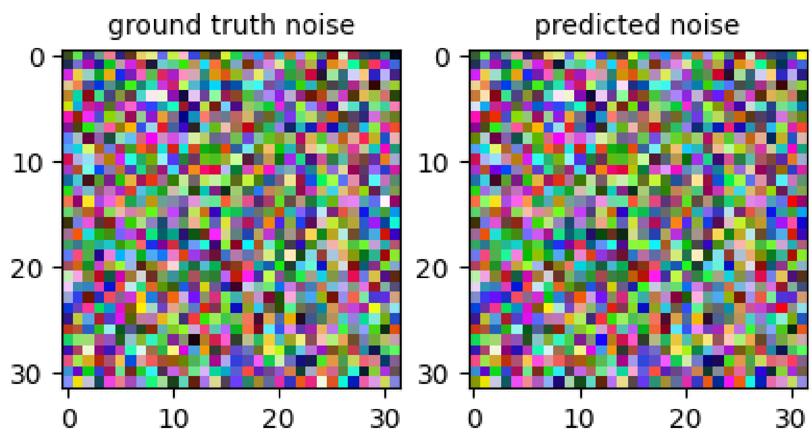
<Figure size 1500x1500 with 0 Axes>

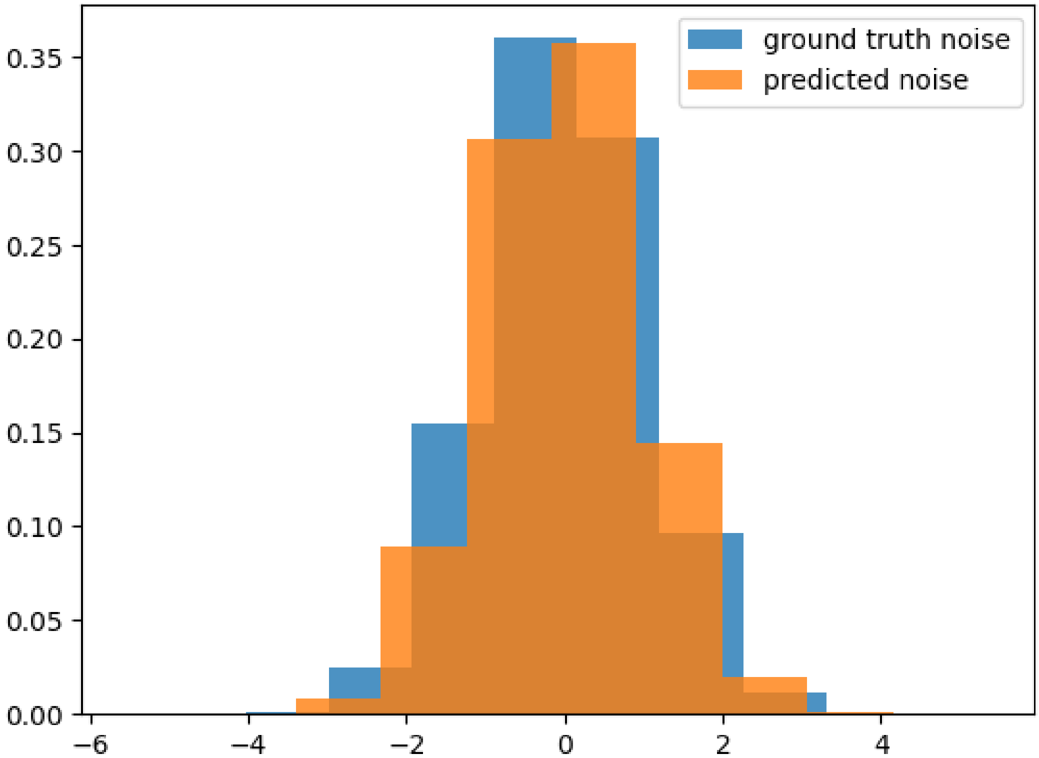




Epoch: 1200 | Train Loss 0.009340619668364525

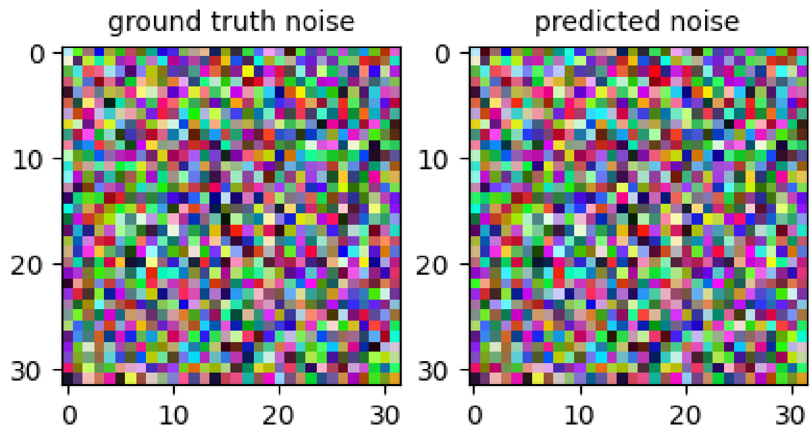
<Figure size 1500x1500 with 0 Axes>

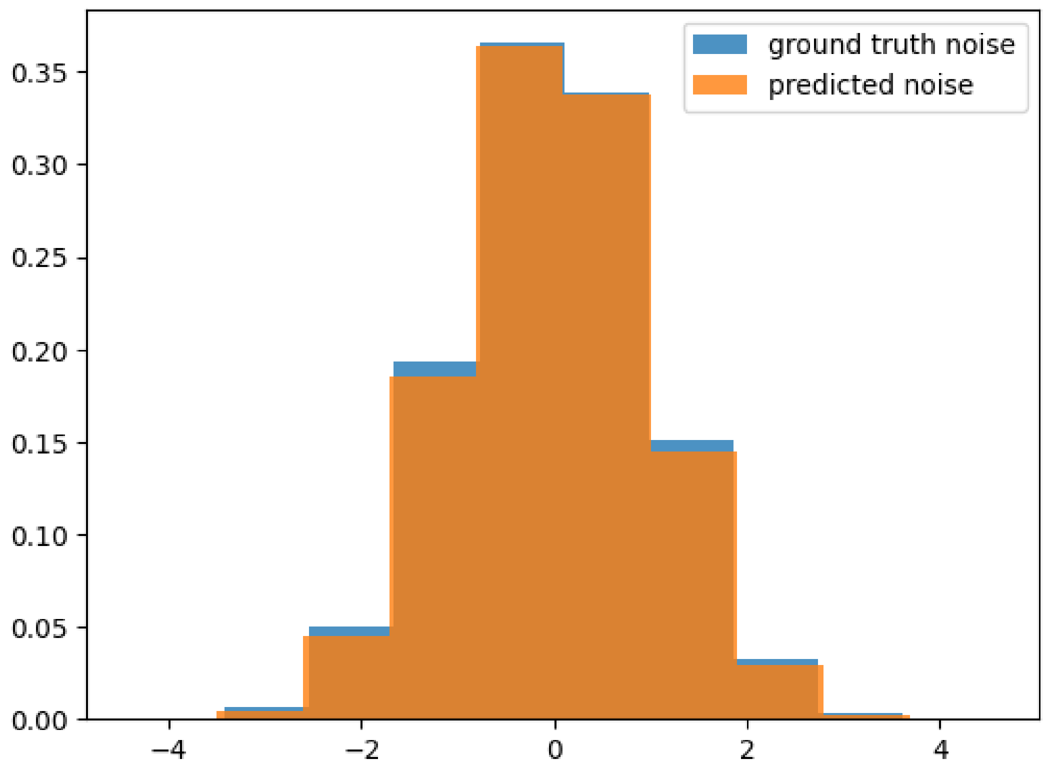




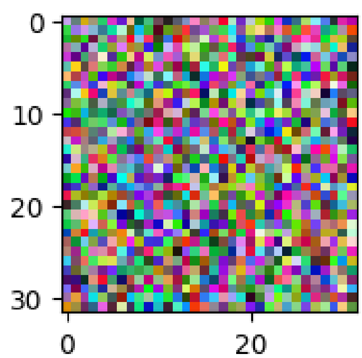
```
Epoch: 1600 | Train Loss 0.005948239937424660
```

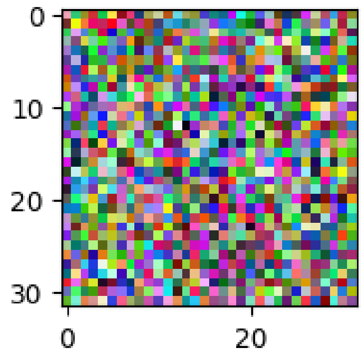
<Figure size 1500x1500 with 0 Axes>

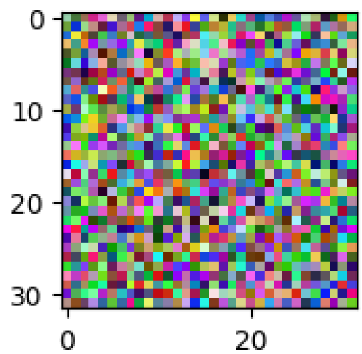


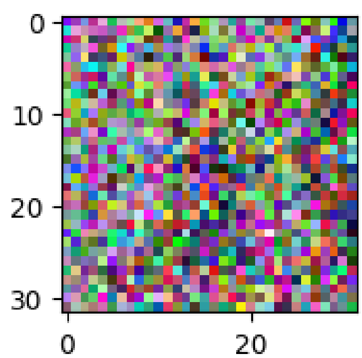


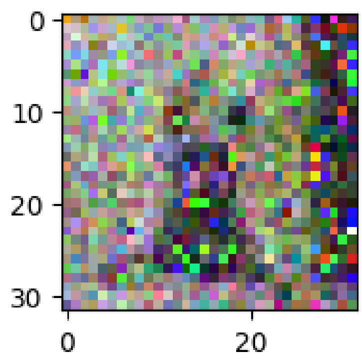
[ ]:
```
with torch.no_grad():
    img = torch.randn((1, 3) + IMAGE_SHAPE).to(device)
    for i in reversed(range(diffusion_model.timesteps)):
        t = torch.full((1,), i, dtype=torch.long, device=device)
        img = diffusion_model.backward(img, t, unet.eval())
        if i % 50 == 0:
            plt.figure(figsize=(2,2))
            plt.imshow(reverse_transform(img[0]))
            plt.show()
```

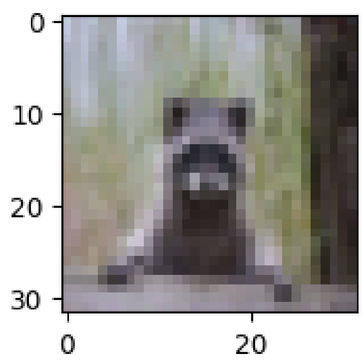












[ ]:
```
BATCH_SIZE = 256
NO_EPOCHS = 100
PRINT_FREQUENCY = 10
LR = 0.001
VERBOSE = False

unet = UNet(labels=True)
unet.to(device)
optimizer = torch.optim.Adam(unet.parameters(), lr=LR)
```

[ ]:
```
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,␣
 ↪download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=BATCH_SIZE,␣
 ↪shuffle=True, num_workers=8, drop_last=True)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,␣
 ↪download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=BATCH_SIZE,␣
 ↪shuffle=False, num_workers=8, drop_last=True)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

```
[ ]: for epoch in range(NO_EPOCHS):
    mean_epoch_loss = []
    mean_epoch_loss_val = []
    for batch, label in trainloader:
        t = torch.randint(0, diffusion_model.timesteps, (BATCH_SIZE,)).long().
 ↪to(device)
        batch = batch.to(device)
        batch_noisy, noise = diffusion_model.forward(batch, t, device)
        predicted_noise = unet(batch_noisy, t, labels = label.reshape(-1,1).
 ↪float().to(device))

        optimizer.zero_grad()
        loss = torch.nn.functional.mse_loss(noise, predicted_noise)
        mean_epoch_loss.append(loss.item())
        loss.backward()
        optimizer.step()

    for batch, label in testloader:

        t = torch.randint(0, diffusion_model.timesteps, (BATCH_SIZE,)).long().
 ↪to(device)
        batch = batch.to(device)

        batch_noisy, noise = diffusion_model.forward(batch, t, device)
        predicted_noise = unet(batch_noisy, t, labels = label.reshape(-1,1).
 ↪float().to(device))

        loss = torch.nn.functional.mse_loss(noise, predicted_noise)
        mean_epoch_loss_val.append(loss.item())

    if epoch % PRINT_FREQUENCY == 0:
        print('---')
        print(f"Epoch: {epoch} | Train Loss {np.mean(mean_epoch_loss)} | Val␣
 ↪Loss {np.mean(mean_epoch_loss_val)}")
        if VERBOSE:
            with torch.no_grad():
                plot_noise_prediction(noise[0], predicted_noise[0])
                plot_noise_distribution(noise, predicted_noise)

        torch.save(unet.state_dict(), f"epoch: {epoch}")
```

```
---
Epoch: 0 | Train Loss 0.17843510527641346 | Val Loss 0.09107233908696052
---
Epoch: 10 | Train Loss 0.06897264002607419 | Val Loss 0.06882068142294884
```

```
---
Epoch: 20 | Train Loss 0.06609276086091995 | Val Loss 0.06503363918417539
---
Epoch: 30 | Train Loss 0.06271165255934764 | Val Loss 0.06314686313271523
---
Epoch: 40 | Train Loss 0.062169487774372104 | Val Loss 0.06125842264065376
---
Epoch: 50 | Train Loss 0.06079999002126547 | Val Loss 0.06021109051429308
---
Epoch: 60 | Train Loss 0.06025462530744381 | Val Loss 0.060078332057366006
---
Epoch: 70 | Train Loss 0.06000458626792981 | Val Loss 0.06053046968120795
---
Epoch: 80 | Train Loss 0.05960569580396016 | Val Loss 0.061160544745433025
---
Epoch: 90 | Train Loss 0.058882863647662674 | Val Loss 0.06030127157767614
```

[ ]:
```
unet = UNet(labels=True)
unet.load_state_dict(torch.load(("epoch: 80")))
```

[ ]: <All keys matched successfully>

[ ]:
```
classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

[ ]:
```
NUM_CLASSES = len(classes)
NUM_DISPLAY_IMAGES = 5
```

[ ]:
```
torch.manual_seed(16)

plt.figure(figsize=(15,15))
f, ax = plt.subplots(NUM_CLASSES, NUM_DISPLAY_IMAGES, figsize = (100,100))

for c in range(NUM_CLASSES):
    imgs = torch.randn((NUM_DISPLAY_IMAGES, 3) + IMAGE_SHAPE).to(device)
    for i in reversed(range(diffusion_model.timesteps)):
        t = torch.full((1,), i, dtype=torch.long, device=device)
        labels = torch.tensor([c] * NUM_DISPLAY_IMAGES).
 ↪resize(NUM_DISPLAY_IMAGES, 1).float().to(device)
        imgs = diffusion_model.backward(x=imgs, t=t, model=unet.eval().
 ↪to(device), labels = labels)
    for idx, img in enumerate(imgs):
        ax[c][idx].imshow(reverse_transform(img))
        ax[c][idx].set_title(f"Class: {classes[c]}", fontsize = 100)

plt.show()
```

```
/home/ubuntu/.local/lib/python3.8/site-packages/torch/_tensor.py:490:
```

```
UserWarning: non-inplace resize is deprecated
  warnings.warn("non-inplace resize is deprecated")
```

<Figure size 1500x1500 with 0 Axes>