diffusion_mnist

January 18, 2025

[8]:
```
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from torchvision import datasets
from torchvision.transforms import Compose, ToTensor, Lambda
from torchsummary import summary
import matplotlib.pyplot as plt
from mpl_toolkits.axes_grid1 import ImageGrid
from tqdm import tqdm
import numpy as np
import imageio.v2 as iio
from IPython.display import display, Image
```

I will be following this training algorithm:

As the parameters of the neural network are shared across time (noise level), I am employing sinusoidal position embeddings to encode t, inspired by Vaswani et al., 2017

Some constants

[9]:
```
BS = 128     # batch size
TIME_EMBEDDING_DIM = 100
TIMESTAMPS = 300
device = "cuda" if torch.cuda.is_available() else "cpu"
```

[10]:
```
# Declaring transformation steps for the dataset
trans = Compose([
    ToTensor(),
    Lambda(lambda t: (t*2) - 1)
])

mnist = datasets.MNIST(root="minist_data/", download=True, transform=trans)

train_dataloader = DataLoader(mnist, batch_size=BS, shuffle=True)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
<urlopen error [Errno 110] Connection timed out>
```

```
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-
idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-
idx3-ubyte.gz to minist_data/MNIST/raw/train-images-idx3-ubyte.gz

100%|     | 9912422/9912422 [00:05<00:00, 1962674.43it/s]

Extracting minist_data/MNIST/raw/train-images-idx3-ubyte.gz to
minist_data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
<urlopen error [Errno 110] Connection timed out>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-
idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-
idx1-ubyte.gz to minist_data/MNIST/raw/train-labels-idx1-ubyte.gz

100%|     | 28881/28881 [00:00<00:00, 62270.16it/s]

Extracting minist_data/MNIST/raw/train-labels-idx1-ubyte.gz to
minist_data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
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idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-
idx3-ubyte.gz to minist_data/MNIST/raw/t10k-images-idx3-ubyte.gz

100%|     | 1648877/1648877 [00:04<00:00, 347520.53it/s]

Extracting minist_data/MNIST/raw/t10k-images-idx3-ubyte.gz to
minist_data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
<urlopen error [Errno 110] Connection timed out>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz to minist_data/MNIST/raw/t10k-labels-idx1-ubyte.gz

100%|     | 4542/4542 [00:00<00:00, 4998826.76it/s]

Extracting minist_data/MNIST/raw/t10k-labels-idx1-ubyte.gz to
minist_data/MNIST/raw
```
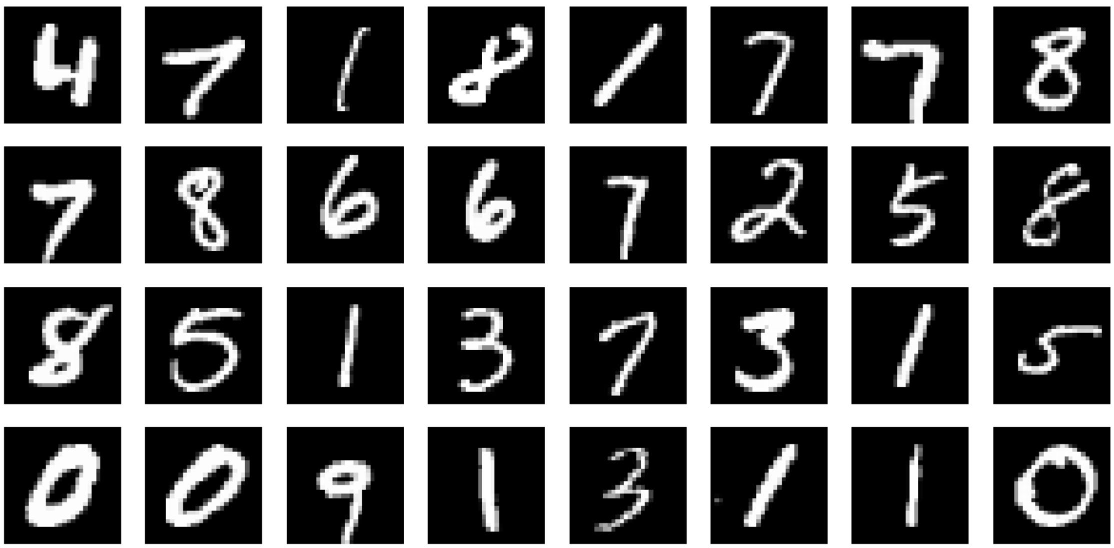

[11]:
```python
def visualize_dataset(dataloader):
  images = next(iter(dataloader))
  plt.figure(figsize=(15,15))
  for i in range(32):
    plt.subplot(8,8,i+1)
    img = np.transpose(images[0][i].numpy(), (1, 2, 0))  # Transpose the image␣
↪dimensions
    plt.imshow(img.squeeze(), cmap='gray')
    plt.axis("off")
```

[12]:
```python
visualize_dataset(train_dataloader)
```



[13]:
```python
# Defining the building blocks of the model

class ConvBlock(nn.Module):
  """Convolution Block."""
  def __init__(self, in_channels, out_channels, kernel_size, stride, padding,␣
↪time_emb_dim, last=False):
    super(ConvBlock, self).__init__()
    self.last = last
    self.time_mlp = nn.Linear(time_emb_dim, in_channels)
    self.conv_layer = nn.Conv2d(in_channels=in_channels,␣
↪out_channels=out_channels, kernel_size=kernel_size, stride=stride,␣
↪padding=padding)
    if not self.last:
      self.batch_norm_layer = nn.BatchNorm2d(out_channels)
      self.act = nn.LeakyReLU()
```

```
  def forward(self, x, t):
    t = self.time_mlp(t)
    x = x + t.view(*t.shape, 1, 1)
    x = self.conv_layer(x)
    if not self.last:
      x = self.batch_norm_layer(x)
      x = self.act(x)
    return x


class UpSampleBlock(nn.Module):
  """Up Sampling Block."""
  def __init__(self, in_channels, out_channels, kernel_size, stride, padding,␣
 ↪output_padding, time_emb_dim, last=False):
    super(UpSampleBlock, self).__init__()
    self.last = last
    self.time_mlp = nn.Linear(time_emb_dim, in_channels)
    self.conv_trans_layer = nn.ConvTranspose2d(in_channels=in_channels,␣
 ↪out_channels=out_channels, kernel_size=kernel_size, stride=stride,␣
 ↪padding=padding, output_padding=output_padding)
    if not self.last:
      self.batch_norm_layer = nn.BatchNorm2d(out_channels)
      self.act = nn.LeakyReLU()

  def forward(self, x, t):
    t = self.time_mlp(t)
    x = x + t.view(*t.shape, 1, 1)
    x = self.conv_trans_layer(x)
    if not self.last:
      x = self.batch_norm_layer(x)
      x = self.act(x)
    return x


class LinearBlock(nn.Module):
  """Linear Block."""
  def __init__(self, in_dim, out_dim, time_emb_dim):
    super(LinearBlock, self).__init__()
    self.time_mlp = nn.Linear(time_emb_dim, in_dim)
    self.linear_layer = nn.Linear(in_dim, out_dim)
    self.batch_norm_layer = nn.BatchNorm1d(out_dim)
    self.act = nn.LeakyReLU()

  def forward(self, x, t):
    t = self.time_mlp(t)
    x = x + t
    x = self.linear_layer(x)
```

```
    x = self.batch_norm_layer(x)
    x = self.act(x)
    return x


class SinusoidalPositionEmbeddings(nn.Module):
    """Encode timestep to dim dimensional vector"""
    def __init__(self, dim):
      super(SinusoidalPositionEmbeddings, self).__init__()
      self.dim = dim

    def forward(self, time):
      device = time.device
      half_dim = self.dim // 2
      embeddings = np.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
```

[14]:
```
class Reshape(nn.Module):
    """A custom reshape layer."""
    def __init__(self, shape):
        super(Reshape, self).__init__()
        self.shape = shape

    def forward(self, x):
        return x.view(*self.shape)


class DiffusionModel(nn.Module):
    """Diffusion model"""
    def __init__(self, time_emb_dim):
        super(DiffusionModel, self).__init__()
        self.time_emb_dim = time_emb_dim

        self.time_embedding_model = nn.Sequential(
            SinusoidalPositionEmbeddings(200),
            nn.Linear(200, time_emb_dim),
            nn.LeakyReLU(),
            nn.Linear(time_emb_dim, time_emb_dim)
        )

        self.dsb_1 = ConvBlock(in_channels=1, out_channels=64, kernel_size=5,␣
 ↪stride=2, padding=2, time_emb_dim=time_emb_dim)
```

```python
        self.conv1 = ConvBlock(in_channels=64, out_channels=128, kernel_size=3, stride=1, padding=1, time_emb_dim=time_emb_dim)
        self.dsb_2 = ConvBlock(in_channels=128, out_channels=256, kernel_size=3, stride=2, padding=1, time_emb_dim=time_emb_dim)

        self.flatten = nn.Flatten(1, -1)

        self.linear_1 = LinearBlock(in_dim=256 * 7 * 7, out_dim=256, time_emb_dim=time_emb_dim)
        self.linear_2 = LinearBlock(in_dim=256, out_dim=128, time_emb_dim=time_emb_dim)
        self.linear_3 = LinearBlock(in_dim=128, out_dim=256 * 7 * 7, time_emb_dim=time_emb_dim)

        self.reshape = Reshape((-1, 256, 7, 7))

        self.usb_1 = UpSampleBlock(in_channels=256, out_channels=128, kernel_size=3, stride=2, padding=1, output_padding=1, time_emb_dim=time_emb_dim)
        self.conv2 = ConvBlock(in_channels=128, out_channels=128, kernel_size=3, stride=1, padding=1, time_emb_dim=time_emb_dim)
        self.usb_2 = UpSampleBlock(in_channels=128, out_channels=64, kernel_size=3, stride=2, padding=1, output_padding=1, time_emb_dim=time_emb_dim)
        self.conv3 = ConvBlock(in_channels=64, out_channels=32, kernel_size=3, stride=1, padding=1, time_emb_dim=time_emb_dim)
        self.conv4 = ConvBlock(in_channels=32, out_channels=1, kernel_size=1, stride=1, padding=0, time_emb_dim=time_emb_dim, last=True)

    def forward(self, x, t):
        t = self.time_embedding_model(t)
        x1 = self.dsb_1(x, t)
        x2 = self.conv1(x1, t)
        x3 = self.dsb_2(x2, t)

        x3_ = self.flatten(x3)
        x4 = self.linear_1(x3_, t)
        x5 = self.linear_2(x4, t)
        x = self.linear_3(x5, t)
        x = self.reshape(x)

        x = self.usb_1(x + x3, t)
        x = self.conv2(x, t)
        x = self.usb_2(x + x2, t)
        x = self.conv3(x, t)
        x = self.conv4(x, t)
```

```
        return x
```

[15]:
```
def linear_beta_schedule(timesteps):
    beta_start = 0.0001
    beta_end = 0.02
    return torch.linspace(beta_start, beta_end, timesteps)

# Define beta schedule
betas = linear_beta_schedule(timesteps=TIMESTAMPS)

# Define alphas
alphas = 1. - betas
alphas_cumprod = torch.cumprod(alphas, axis=0)
alphas_cumprod_prev = nn.functional.pad(alphas_cumprod[:-1], (1, 0), value=1.0)
sqrt_recip_alphas = torch.sqrt(1.0 / alphas)

# Calculations for diffusion q(x_t | x_{t-1}) and others
sqrt_alphas_cumprod = torch.sqrt(alphas_cumprod)
sqrt_one_minus_alphas_cumprod = torch.sqrt(1. - alphas_cumprod)

# Calculations for posterior q(x_{t-1} | x_t, x_0)
posterior_variance = betas * (1. - alphas_cumprod_prev) / (1. - alphas_cumprod)

def extract(a, t, x_shape):
    batch_size = t.shape[0]
    out = a.gather(-1, t.cpu())
    return out.reshape(batch_size, *((1,) * (len(x_shape) - 1))).to(t.device)
```

[16]:
```
# Forward diffusion
def q_sample(x_start, t, noise=None):
    if noise is None:
        noise = torch.randn_like(x_start)

    sqrt_alphas_cumprod_t = extract(sqrt_alphas_cumprod, t, x_start.shape)
    sqrt_one_minus_alphas_cumprod_t = extract(
        sqrt_one_minus_alphas_cumprod, t, x_start.shape
    )

    return sqrt_alphas_cumprod_t * x_start + sqrt_one_minus_alphas_cumprod_t *␣
 ↪noise
```

[17]:
```
def p_losses(denoise_model, x_start, t, noise=None):
    if noise is None:
        noise = torch.randn_like(x_start)

    x_noisy = q_sample(x_start=x_start, t=t, noise=noise)
```

```
    predicted_noise = denoise_model(x_noisy, t)

    loss = nn.functional.smooth_l1_loss(noise, predicted_noise)

    return loss
```

[18]:
```
def train(net, epochs, lr):

    optimizer = torch.optim.Adam(net.parameters(), lr)

    # Training loop
    for i in range(1,epochs+1):
        running_loss = 0
        pbar = tqdm(train_dataloader)
        for b, data in enumerate(pbar):
            # Every data instance is an input + label pair. We don't need the␣
↪label
            inputs, _ = data
            inputs = inputs.to(device)

            # Zero the gradients for every batch!
            optimizer.zero_grad()

            t = torch.randint(0, TIMESTAMPS, (inputs.shape[0],), device=device).
↪long()

            # Compute the loss and its gradients
            loss = p_losses(net, inputs, t)
            loss.backward()

            # Adjust learning weights
            optimizer.step()

            # Update Progress
            running_loss += loss.item()
            pbar.set_description(f"Epoch {i}/{epochs}: ")
            pbar.set_postfix({"batch_loss": loss.item(), "avg_loss":␣
↪running_loss/(b+1)})
```

[19]:
```
net = DiffusionModel(time_emb_dim=TIME_EMBEDDING_DIM)
net.to(device)
```

[19]:
```
DiffusionModel(
  (time_embedding_model): Sequential(
    (0): SinusoidalPositionEmbeddings()
    (1): Linear(in_features=200, out_features=100, bias=True)
    (2): LeakyReLU(negative_slope=0.01)
```

```
    (3): Linear(in_features=100, out_features=100, bias=True)
  )
  (dsb_1): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=1, bias=True)
    (conv_layer): Conv2d(1, 64, kernel_size=(5, 5), stride=(2, 2), padding=(2,
2))
    (batch_norm_layer): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (conv1): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=64, bias=True)
    (conv_layer): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (batch_norm_layer): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (dsb_2): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=128, bias=True)
    (conv_layer): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1))
    (batch_norm_layer): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (linear_1): LinearBlock(
    (time_mlp): Linear(in_features=100, out_features=12544, bias=True)
    (linear_layer): Linear(in_features=12544, out_features=256, bias=True)
    (batch_norm_layer): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (linear_2): LinearBlock(
    (time_mlp): Linear(in_features=100, out_features=256, bias=True)
    (linear_layer): Linear(in_features=256, out_features=128, bias=True)
    (batch_norm_layer): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (linear_3): LinearBlock(
    (time_mlp): Linear(in_features=100, out_features=128, bias=True)
    (linear_layer): Linear(in_features=128, out_features=12544, bias=True)
    (batch_norm_layer): BatchNorm1d(12544, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
```

```
  )
  (reshape): Reshape()
  (usb_1): UpSampleBlock(
    (time_mlp): Linear(in_features=100, out_features=256, bias=True)
    (conv_trans_layer): ConvTranspose2d(256, 128, kernel_size=(3, 3), stride=(2,
2), padding=(1, 1), output_padding=(1, 1))
    (batch_norm_layer): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (conv2): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=128, bias=True)
    (conv_layer): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1))
    (batch_norm_layer): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (usb_2): UpSampleBlock(
    (time_mlp): Linear(in_features=100, out_features=128, bias=True)
    (conv_trans_layer): ConvTranspose2d(128, 64, kernel_size=(3, 3), stride=(2,
2), padding=(1, 1), output_padding=(1, 1))
    (batch_norm_layer): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (conv3): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=64, bias=True)
    (conv_layer): Conv2d(64, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (batch_norm_layer): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (act): LeakyReLU(negative_slope=0.01)
  )
  (conv4): ConvBlock(
    (time_mlp): Linear(in_features=100, out_features=32, bias=True)
    (conv_layer): Conv2d(32, 1, kernel_size=(1, 1), stride=(1, 1))
  )
)
```

[20]:

```
train(net, 50, 1e-3)
```

```
Epoch 1/50: : 100%|      | 469/469 [00:14<00:00, 33.11it/s,
batch_loss=0.0349, avg_loss=0.0585]
Epoch 2/50: : 100%|      | 469/469 [00:12<00:00, 36.91it/s,
batch_loss=0.0313, avg_loss=0.0332]
Epoch 3/50: : 100%|      | 469/469 [00:12<00:00, 37.33it/s,
```

```
batch_loss=0.0278, avg_loss=0.0292]
Epoch 4/50: : 100%|     | 469/469 [00:12<00:00, 37.39it/s,
batch_loss=0.0217, avg_loss=0.0274]
Epoch 5/50: : 100%|     | 469/469 [00:12<00:00, 37.67it/s,
batch_loss=0.0254, avg_loss=0.0259]
Epoch 6/50: : 100%|     | 469/469 [00:12<00:00, 37.57it/s,
batch_loss=0.0254, avg_loss=0.0252]
Epoch 7/50: : 100%|     | 469/469 [00:11<00:00, 39.09it/s,
batch_loss=0.025, avg_loss=0.0247]
Epoch 8/50: : 100%|     | 469/469 [00:11<00:00, 39.46it/s,
batch_loss=0.0198, avg_loss=0.0241]
Epoch 9/50: : 100%|     | 469/469 [00:11<00:00, 39.39it/s,
batch_loss=0.0222, avg_loss=0.0239]
Epoch 10/50: : 100%|     | 469/469 [00:11<00:00, 39.43it/s,
batch_loss=0.0196, avg_loss=0.0233]
Epoch 11/50: : 100%|     | 469/469 [00:12<00:00, 38.21it/s,
batch_loss=0.0272, avg_loss=0.0229]
Epoch 12/50: : 100%|     | 469/469 [00:12<00:00, 38.89it/s,
batch_loss=0.0224, avg_loss=0.0228]
Epoch 13/50: : 100%|     | 469/469 [00:11<00:00, 39.09it/s,
batch_loss=0.0194, avg_loss=0.0224]
Epoch 14/50: : 100%|     | 469/469 [00:11<00:00, 39.23it/s,
batch_loss=0.0236, avg_loss=0.0223]
Epoch 15/50: : 100%|     | 469/469 [00:12<00:00, 37.59it/s,
batch_loss=0.0247, avg_loss=0.0224]
Epoch 16/50: : 100%|     | 469/469 [00:12<00:00, 37.11it/s,
batch_loss=0.0217, avg_loss=0.0219]
Epoch 17/50: : 100%|     | 469/469 [00:12<00:00, 36.37it/s,
batch_loss=0.0205, avg_loss=0.022]
Epoch 18/50: : 100%|     | 469/469 [00:12<00:00, 36.44it/s,
batch_loss=0.02, avg_loss=0.0218]
Epoch 19/50: : 100%|     | 469/469 [00:12<00:00, 36.37it/s,
batch_loss=0.0193, avg_loss=0.0216]
Epoch 20/50: : 100%|     | 469/469 [00:12<00:00, 36.31it/s,
batch_loss=0.0237, avg_loss=0.0215]
Epoch 21/50: : 100%|     | 469/469 [00:13<00:00, 36.07it/s,
batch_loss=0.021, avg_loss=0.0216]
Epoch 22/50: : 100%|     | 469/469 [00:13<00:00, 35.06it/s,
batch_loss=0.0189, avg_loss=0.0211]
Epoch 23/50: : 100%|     | 469/469 [00:12<00:00, 36.94it/s,
batch_loss=0.0224, avg_loss=0.0214]
Epoch 24/50: : 100%|     | 469/469 [00:12<00:00, 37.34it/s,
batch_loss=0.0218, avg_loss=0.0213]
Epoch 25/50: : 100%|     | 469/469 [00:12<00:00, 36.94it/s,
batch_loss=0.0193, avg_loss=0.0211]
Epoch 26/50: : 100%|     | 469/469 [00:12<00:00, 36.36it/s,
batch_loss=0.0205, avg_loss=0.0209]
Epoch 27/50: : 100%|     | 469/469 [00:12<00:00, 37.26it/s,
```

```
batch_loss=0.021, avg_loss=0.021]
Epoch 28/50: : 100%|      | 469/469 [00:12<00:00, 36.51it/s,
batch_loss=0.0191, avg_loss=0.0207]
Epoch 29/50: : 100%|      | 469/469 [00:12<00:00, 37.60it/s,
batch_loss=0.0228, avg_loss=0.0208]
Epoch 30/50: : 100%|      | 469/469 [00:12<00:00, 37.67it/s,
batch_loss=0.02, avg_loss=0.0207]
Epoch 31/50: : 100%|      | 469/469 [00:12<00:00, 37.18it/s,
batch_loss=0.0252, avg_loss=0.0207]
Epoch 32/50: : 100%|      | 469/469 [00:13<00:00, 35.88it/s,
batch_loss=0.0182, avg_loss=0.0207]
Epoch 33/50: : 100%|      | 469/469 [00:12<00:00, 37.94it/s,
batch_loss=0.0208, avg_loss=0.0205]
Epoch 34/50: : 100%|      | 469/469 [00:12<00:00, 37.22it/s,
batch_loss=0.0214, avg_loss=0.0205]
Epoch 35/50: : 100%|      | 469/469 [00:12<00:00, 36.95it/s,
batch_loss=0.0194, avg_loss=0.0203]
Epoch 36/50: : 100%|      | 469/469 [00:12<00:00, 37.26it/s,
batch_loss=0.0187, avg_loss=0.0204]
Epoch 37/50: : 100%|      | 469/469 [00:12<00:00, 36.65it/s,
batch_loss=0.0191, avg_loss=0.0204]
Epoch 38/50: : 100%|      | 469/469 [00:12<00:00, 36.67it/s,
batch_loss=0.0213, avg_loss=0.0203]
Epoch 39/50: : 100%|      | 469/469 [00:12<00:00, 37.65it/s,
batch_loss=0.0187, avg_loss=0.0203]
Epoch 40/50: : 100%|      | 469/469 [00:12<00:00, 37.80it/s,
batch_loss=0.0215, avg_loss=0.0201]
Epoch 41/50: : 100%|      | 469/469 [00:12<00:00, 37.45it/s,
batch_loss=0.0189, avg_loss=0.0203]
Epoch 42/50: : 100%|      | 469/469 [00:12<00:00, 37.83it/s,
batch_loss=0.0201, avg_loss=0.02]
Epoch 43/50: : 100%|      | 469/469 [00:12<00:00, 37.69it/s,
batch_loss=0.0231, avg_loss=0.0202]
Epoch 44/50: : 100%|      | 469/469 [00:12<00:00, 37.35it/s,
batch_loss=0.0194, avg_loss=0.02]
Epoch 45/50: : 100%|      | 469/469 [00:12<00:00, 36.78it/s,
batch_loss=0.0188, avg_loss=0.02]
Epoch 46/50: : 100%|      | 469/469 [00:13<00:00, 35.75it/s,
batch_loss=0.0208, avg_loss=0.02]
Epoch 47/50: : 100%|      | 469/469 [00:12<00:00, 37.15it/s,
batch_loss=0.019, avg_loss=0.0199]
Epoch 48/50: : 100%|      | 469/469 [00:12<00:00, 37.89it/s,
batch_loss=0.0198, avg_loss=0.0198]
Epoch 49/50: : 100%|      | 469/469 [00:12<00:00, 38.04it/s,
batch_loss=0.019, avg_loss=0.0199]
Epoch 50/50: : 100%|      | 469/469 [00:12<00:00, 37.11it/s,
batch_loss=0.0192, avg_loss=0.0198]
```

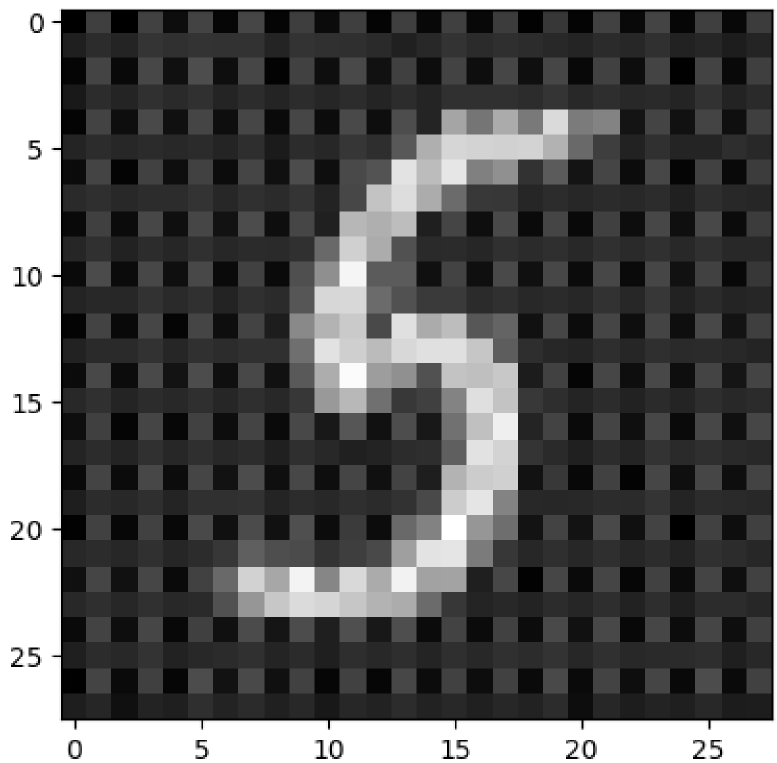
[21]:
```
@torch.no_grad()
def p_sample(model, x, t, t_index):
    betas_t = extract(betas, t, x.shape)
    sqrt_one_minus_alphas_cumprod_t = extract(
        sqrt_one_minus_alphas_cumprod, t, x.shape
    )
    sqrt_recip_alphas_t = extract(sqrt_recip_alphas, t, x.shape)

    # Equation 11 in the paper
    # Use our model (noise predictor) to predict the mean
    model_mean = sqrt_recip_alphas_t * (
        x - betas_t * model(x, t) / sqrt_one_minus_alphas_cumprod_t
    )

    if t_index == 0:
        return model_mean
    else:
        posterior_variance_t = extract(posterior_variance, t, x.shape)
        noise = torch.randn_like(x)
        # Algorithm 2 line 4:
        return model_mean + torch.sqrt(posterior_variance_t) * noise

# Algorithm 2 (including returning all images)
@torch.no_grad()
def p_sample_loop(model, shape):
    device = next(model.parameters()).device

    b = shape[0]
    # start from pure noise (for each example in the batch)
    img = torch.randn(shape, device=device)
    imgs = []

    for i in tqdm(reversed(range(0, TIMESTAMPS)), desc='sampling loop time␣
↪step', total=TIMESTAMPS):
        img = p_sample(model, img, torch.full((b,), i, device=device,␣
↪dtype=torch.long), i)
        imgs.append(img.cpu().numpy())
    return imgs

@torch.no_grad()
def sample(model, image_size, batch_size=16, channels=3):
    return p_sample_loop(model, shape=(batch_size, channels, image_size,␣
↪image_size))
```

[22]:
```
# sample 64 images
samples = sample(net, image_size=28, batch_size=64, channels=1)
```

```
# show a random one
random_index = 0
plt.imshow(samples[-1][random_index].reshape(28, 28), cmap="gray")
```

```
sampling loop time step: 100%|          | 300/300 [00:01<00:00, 226.74it/s]
```

[22]: <matplotlib.image.AxesImage at 0x73b5769d2b50>



[24]:
```
random_index = 53

# Collect image data in the proper format
ims = []
for i in range(TIMESTAMPS):
    img = samples[i][random_index].squeeze()  # Squeeze to remove␣
 ↪single-dimensional entries from the shape
    ims.append(img)

# Scale images to desired size (e.g., double the size)
scaled_ims = [np.kron(img, np.ones((6, 6))) for img in ims]  # Example: Double␣
 ↪the size using np.kron

# Normalize pixel values to range [0, 255]
```

```
scaled_ims = [(img - np.min(img)) / (np.max(img) - np.min(img)) * 255 for img␣
 ↪in scaled_ims]
scaled_ims = [img.astype(np.uint8) for img in scaled_ims]

iio.mimsave('generated_images.gif', scaled_ims, duration=0.1)

with open('generated_images.gif', 'rb') as f:
    display(Image(data=f.read(), format='gif'))
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[24], line 16
     13 scaled_ims = [(img - np.min(img)) / (np.max(img) - np.min(img)) * 255␣
 ↪for img in scaled_ims]
     14 scaled_ims = [img.astype(np.uint8) for img in scaled_ims]
---> 16 iio.mimsave('generated_images.gif', scaled_ims, duration=0.1)
     18 with open('generated_images.gif', 'rb') as f:
     19     display(Image(data=f.read(), format='gif'))

File /media/chris/UBUNTU_PARTITION/anaconda3/envs/dualstylegan_env/lib/python3.8/
 ↪site-packages/imageio/v2.py:494, in mimwrite(uri, ims, format, **kwargs)
    492 imopen_args = decypher_format_arg(format)
    493 imopen_args["legacy_mode"] = True
--> 494 with imopen(uri, "wI", **imopen_args) as file:
    495     return file.write(ims, is_batch=True, **kwargs)

File /media/chris/UBUNTU_PARTITION/anaconda3/envs/dualstylegan_env/lib/python3.8/
 ↪site-packages/imageio/core/imopen.py:198, in imopen(uri, io_mode, plugin,␣
 ↪legacy_mode, **kwargs)
    195 try:
    196     plugin_instance = candidate_plugin(request, **kwargs)
    197 except InitializationError:
--> 198     # file extension doesn't match file type
    199     continue
    201 return plugin_instance

TypeError: partial_legacy_plugin() got an unexpected keyword argument 'extension'
```