LAB 7:
GENERATIVE ADVERSARIAL NETWORKS

University of Washington, Seattle

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OUTLINE

Part 1: Generative Adversarial Networks

- GAN Architecture
- Generator
- Discriminator

Part 2: Constructing GAN in PyTorch

- Competing loss function
- Two-player game optimization PyTorch

Part 3: GAN applications

- MNIST generation with Vanilla GAN

Part 4: Generator Extension with Convolution

- Upscaling with 2D transpose convolution

Part 4: Lab Assignment

- MNIST generation with DCGAN

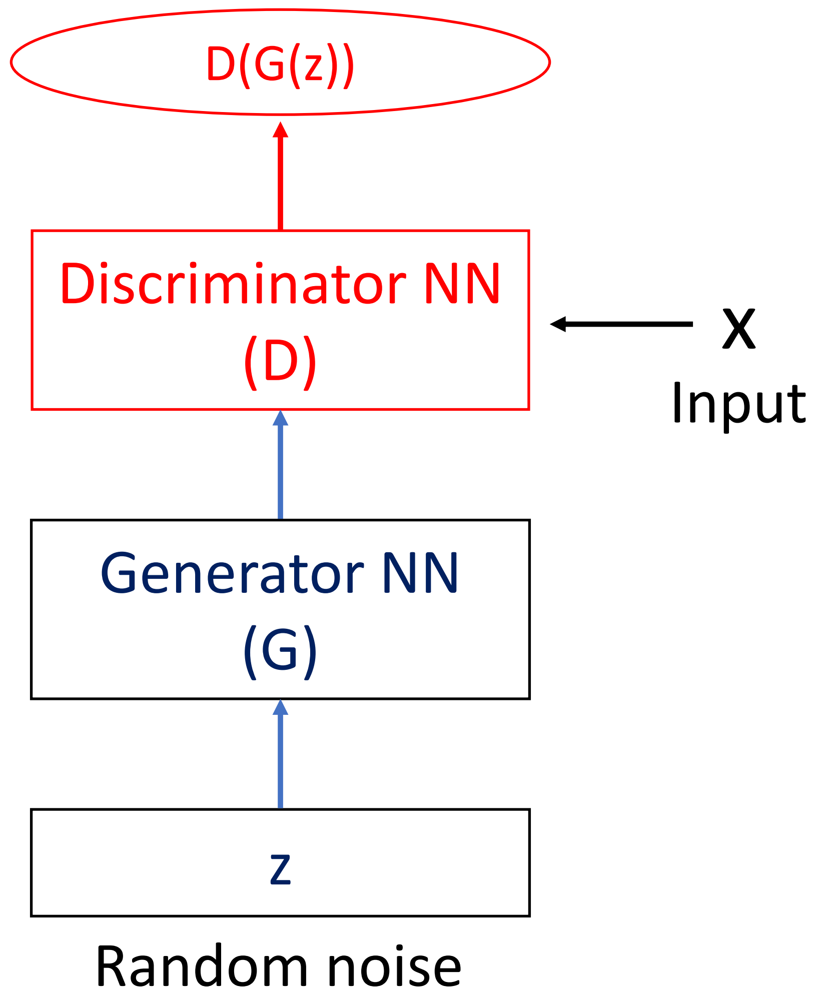
Generative Adversarial Networks

GAN Architecture

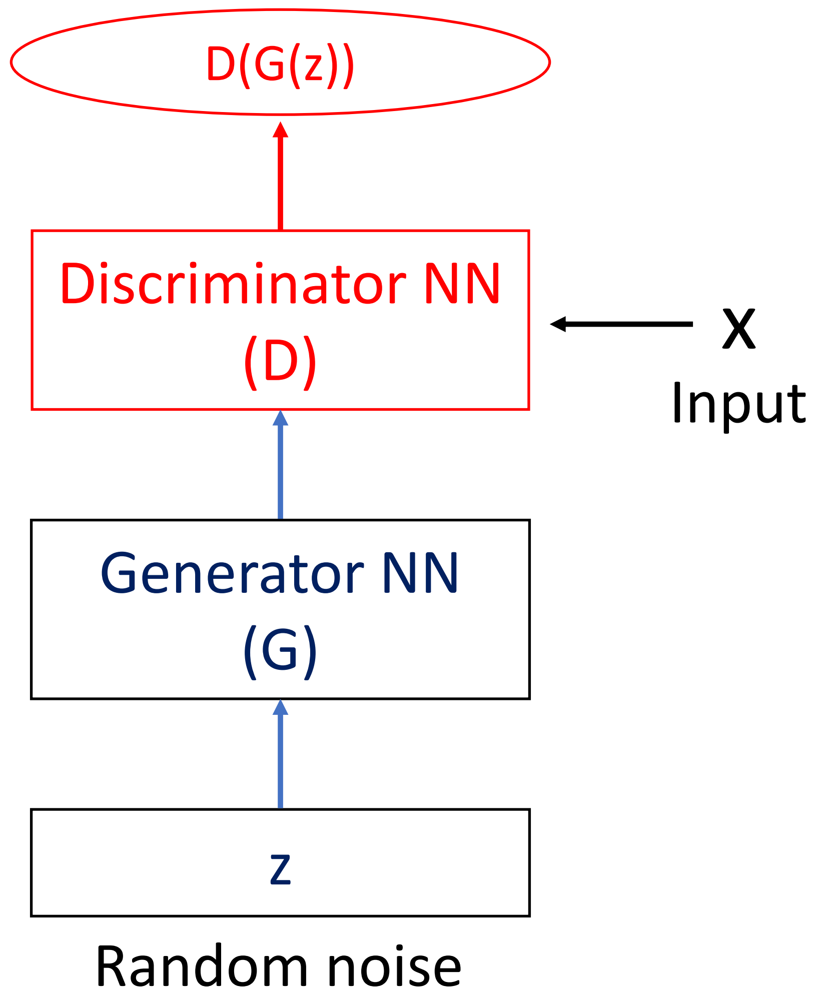
Generator

Discriminator

GAN



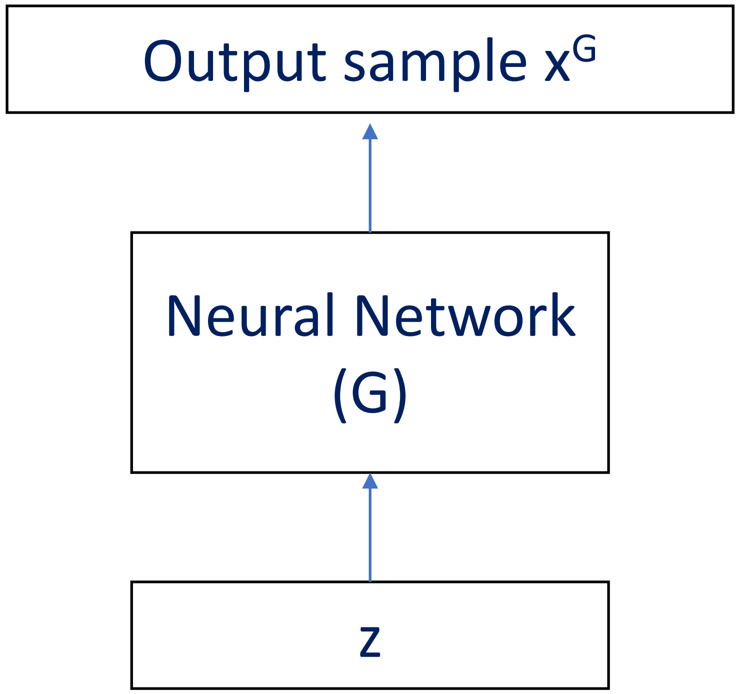
GAN



Discriminator – try to distinguish between **x (real) and generated (fake)** images

Generator – try to generate **samples and present them as real world** and fool the discriminator

Generator (G)



Training data has distribution $\mathbf{p}_{\mathbf{data.}}$
Sample $\mathbf{x} \sim \mathbf{p}_{\mathbf{data.}}$

Require: Output sample $\mathbf{x}^{\mathbf{G}}$ is of similar dimensions as $\mathbf{x}$ and distribution $\mathbf{p}_{\mathbf{data.}}$

Examples

Face:

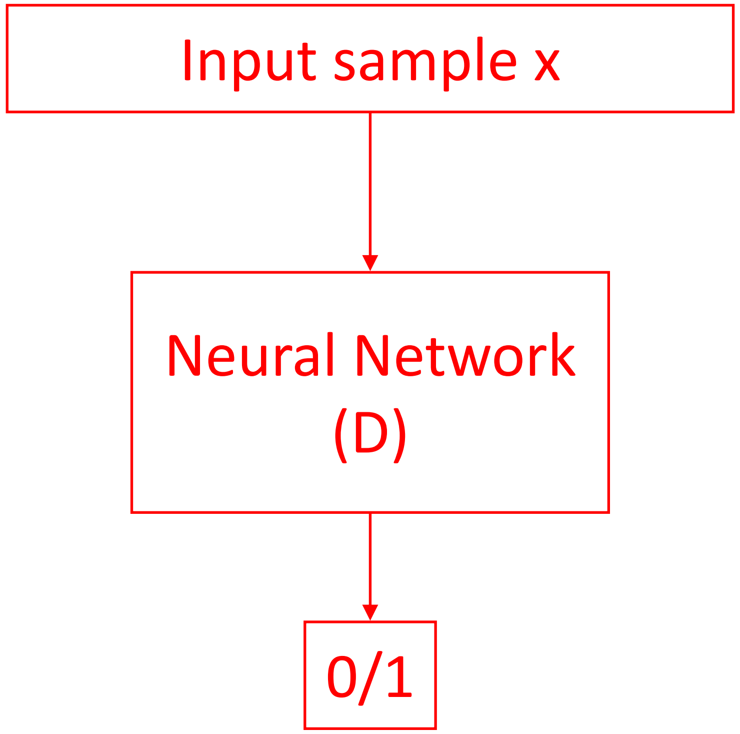
Tesla Car:

Bedroom:

Discriminator (D)

Receives input of same dimensions as $\mathbf{p}_{\mathbf{data}}$.

Determine: is sample from $\mathbf{p}_{\mathbf{data}}$ (1) or not (0).



Examples

Discriminator

Face:

0

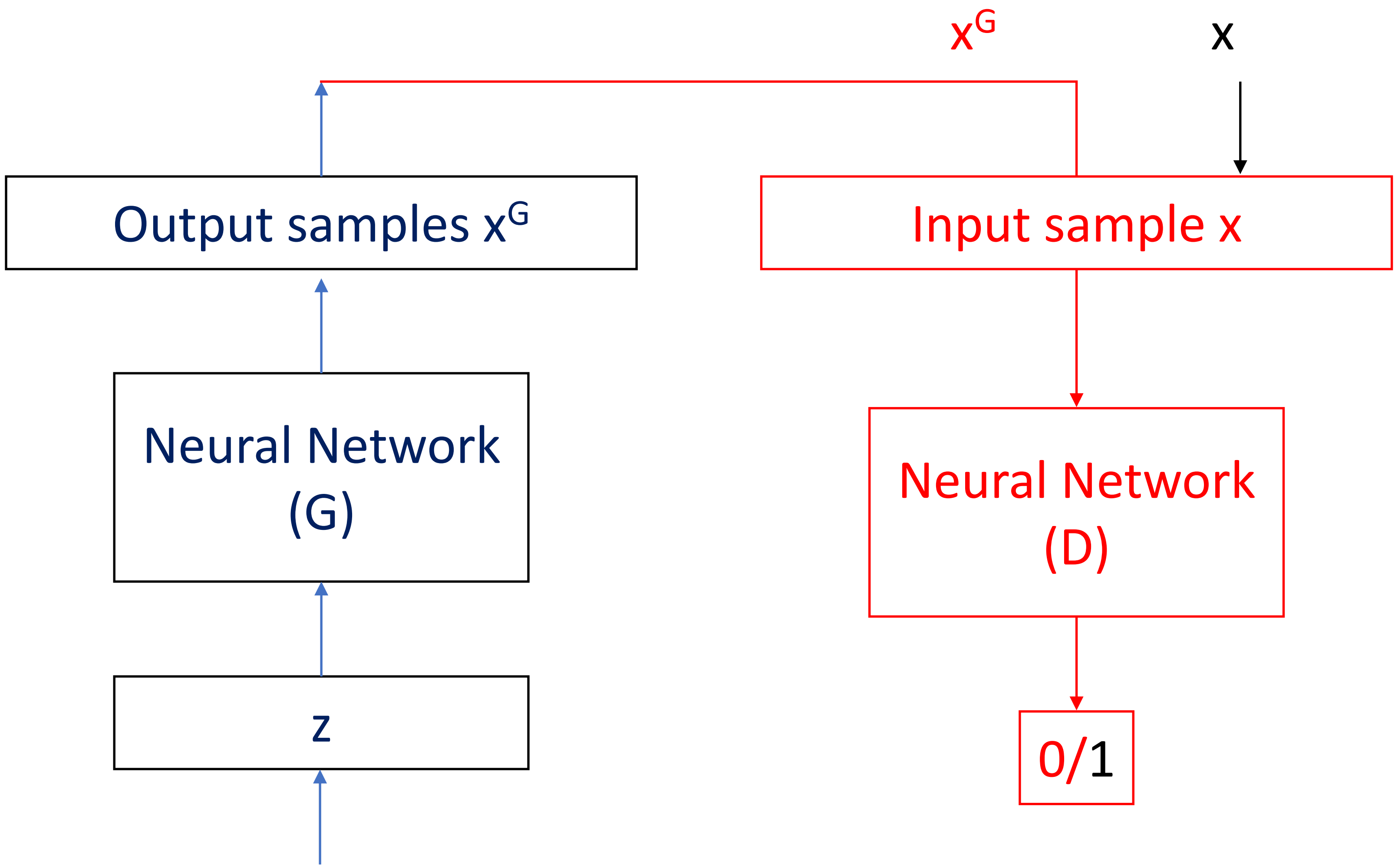
Tesla Car:

0

Bedroom:

0

Full Architecture



GAN Optimization and Applications

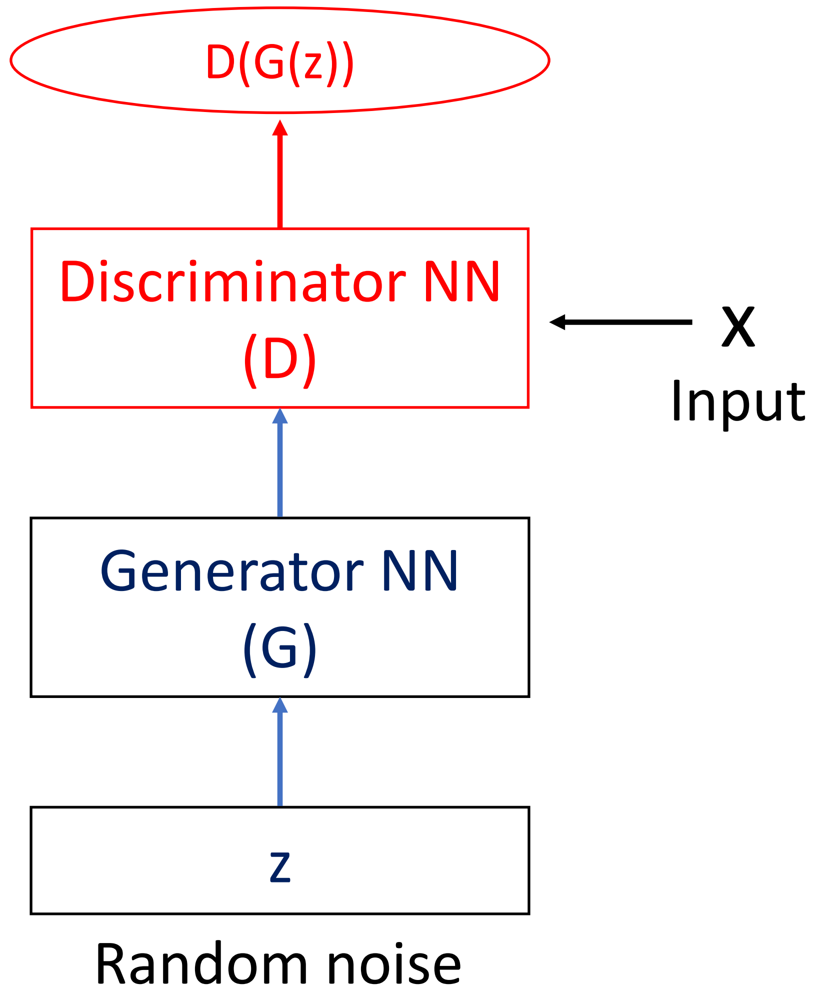
Competing loss function

Two-player game optimization PyTorch

Competing cost functions

“Cost”: $\|D(G(z))\|$

“Cost”: $\|D(G(z)) - 1\|$



Competing cost functions

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) - \frac{1}{2}\mathbb{E}_{z\sim p_{model}} \log\left(1 - D_{\theta_d}(G_{\theta_g}(z))\right)$$

$$J^{(G)} = -J^{(D)}$$

$$J^{(D)} = -\frac{1}{2}\int p_{data}(x) \log D(x) dx - \frac{1}{2}\int p_{model}(x) \log\big(1 - D(x)\big) dx$$

Minmax Game Optimization

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p_{model}} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Discriminator output for real data

Discriminator output for generated data

Solution:

- Saddle point in the parameter space (Nash Equillibrium)

Optimization in NN

Gradient ascent for the discriminator on J

$$J^{(D)} = \frac{1}{2}\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \frac{1}{2}\mathbb{E}_{z\sim p_{model}} \log\left(1 - D_{\theta_d}(G_{\theta_g}(z))\right)$$

$$\theta_d \leftarrow \underset{\theta_d}{\arg\min}\, J^{(D)}$$

Gradient descent for the generator

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{z\sim p_{model}} \log\left(1 - D_{\theta_d}(G_{\theta_g}(z))\right)$$

$$\theta_g \leftarrow \underset{\theta_g}{\arg\min}\, J^{(G)}$$

Optimization in NN

```
For epoch in range(epochs):
    For batch in batches:
        Compute $D_{\theta_d}(x)$ vs Real labels
        Compute $D_{\theta_d}(G_{\theta_g}(z))$ vs Fake labels
        Compute $J^{(D)}$

        Backpropagation
        Update network
```

Discriminator Network

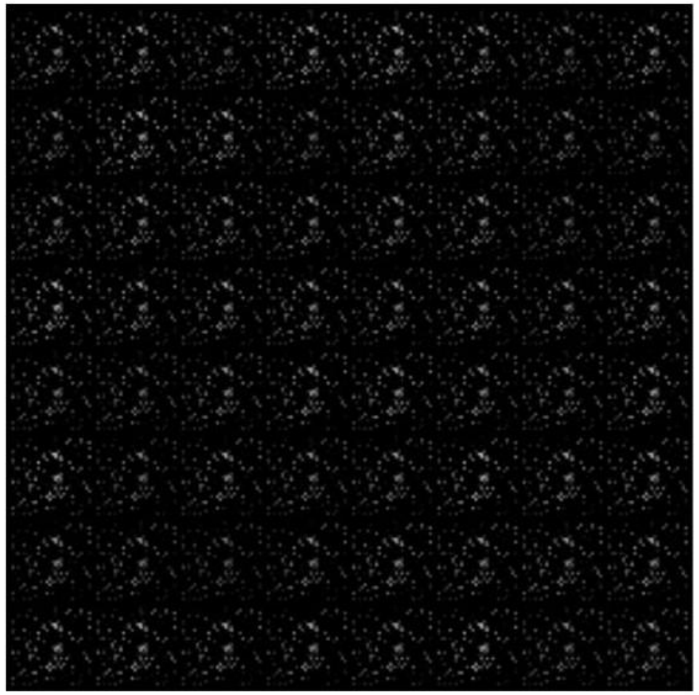
```
For epoch in range(epochs):
    For batch in batches:
        Compute $D_{\theta_d}(G_{\theta_g}(z))$ vs Real labels
        Compute $J^{(G)}$

        Backpropagation
        Update network
```

Generator Network

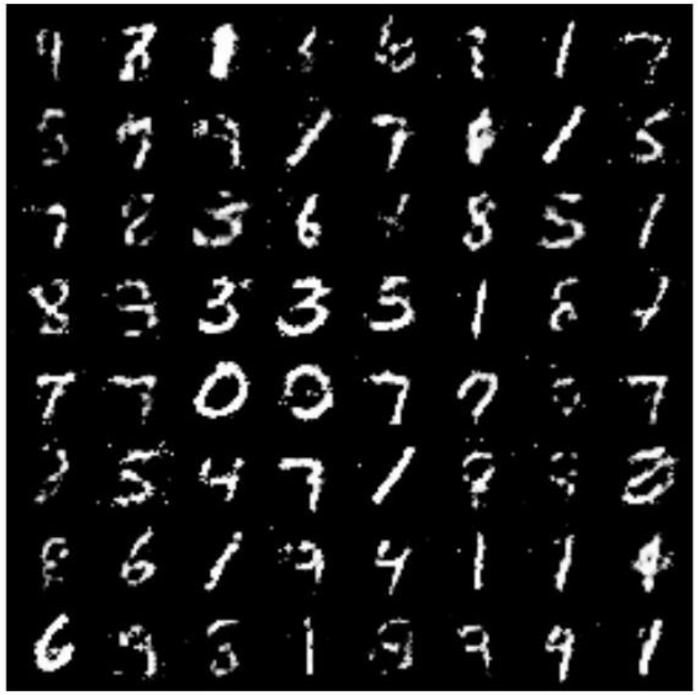
GAN Applications:

MNIST Generation with Vanilla GAN

MNIST Generation with GAN

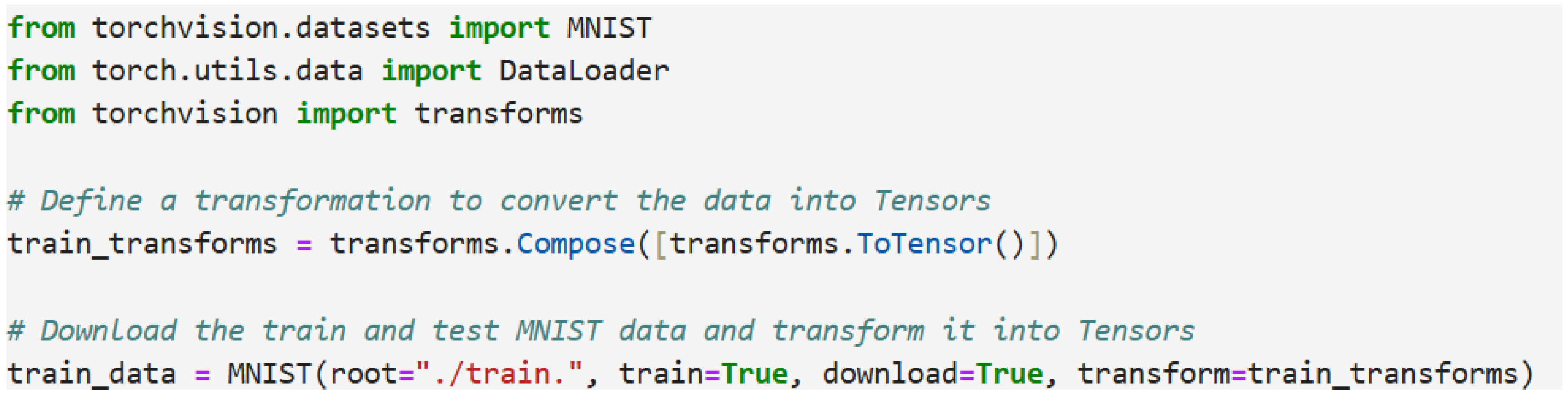


Before Training



After Training

Prepare Data



```python
from torchvision.datasets import MNIST
from torch.utils.data import DataLoader
from torchvision import transforms

# Define a transformation to convert the data into Tensors
train_transforms = transforms.Compose([transforms.ToTensor()])

# Download the train and test MNIST data and transform it into Tensors
train_data = MNIST(root="./train.", train=True, download=True, transform=train_transforms)
```

Load MNIST dataset and in built DataLoader from torch

Configure the data transformation (to PyTorch tensors)

Download the training and testing data
N = 60000

Define Model (Generator)

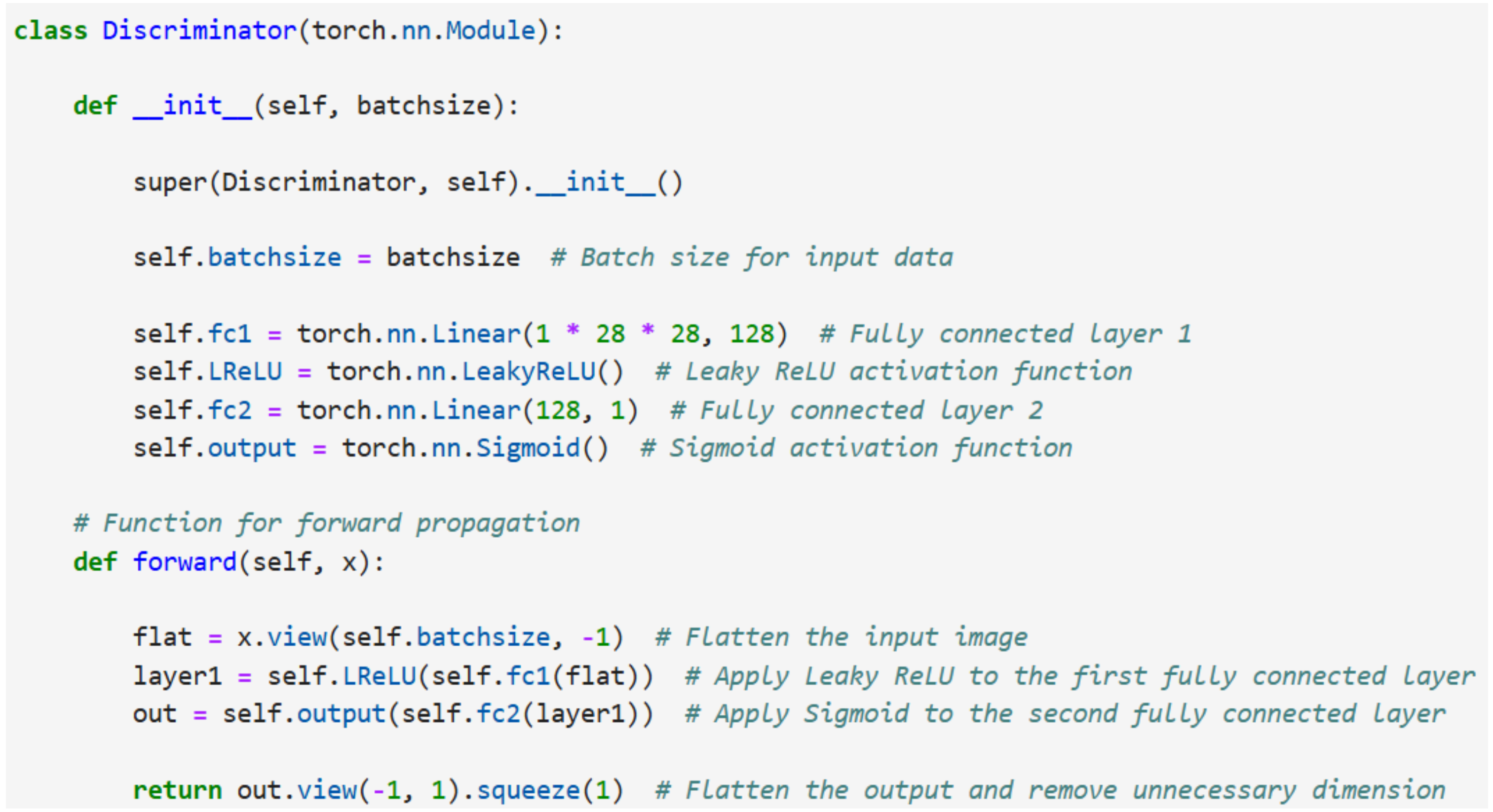
```python
class Generator(torch.nn.Module):

    def __init__(self, batchsize, input_noise_dim):

        super(Generator, self).__init__()

        self.batchsize = batchsize  # Batch size for input data
        self.input_noise_dim = input_noise_dim  # Dimension of the input data

        self.fc1 = torch.nn.Linear(input_noise_dim, 128)  # Fully connected layer 1
        self.LReLU = torch.nn.LeakyReLU()  # Leaky ReLU activation function
        self.fc2 = torch.nn.Linear(128, 1 * 28 * 28)  # Fully connected layer 2
        self.output = torch.nn.Tanh()  # Hyperbolic Tangent activation function

    def forward(self, x):

        layer1 = self.LReLU(self.fc1(x))  # Apply Leaky ReLU to the first fully connected layer
        layer2 = self.output(self.fc2(layer1))  # Apply Tanh to the second fully connected layer
        out = layer2.view(self.batchsize, 1, 28, 28)  # Reshape the output to match image dimensions

        return out
```

Takes batchsize and input noise dimension as inputs

Define FC1, FC2 layers
Uses LeakyReLU() as hidden layer activation
Uses Tanh() as output layer activation

Define signal propagation
input noise -> FC1 -> FC2 -> Output

Define Model (Discriminator)



```python
class Discriminator(torch.nn.Module):

    def __init__(self, batchsize):

        super(Discriminator, self).__init__()

        self.batchsize = batchsize  # Batch size for input data

        self.fc1 = torch.nn.Linear(1 * 28 * 28, 128)  # Fully connected layer 1
        self.LReLU = torch.nn.LeakyReLU()  # Leaky ReLU activation function
        self.fc2 = torch.nn.Linear(128, 1)  # Fully connected layer 2
        self.output = torch.nn.Sigmoid()  # Sigmoid activation function

    # Function for forward propagation
    def forward(self, x):

        flat = x.view(self.batchsize, -1)  # Flatten the input image
        layer1 = self.LReLU(self.fc1(flat))  # Apply Leaky ReLU to the first fully connected layer
        out = self.output(self.fc2(layer1))  # Apply Sigmoid to the second fully connected layer

        return out.view(-1, 1).squeeze(1)  # Flatten the output and remove unnecessary dimension
```

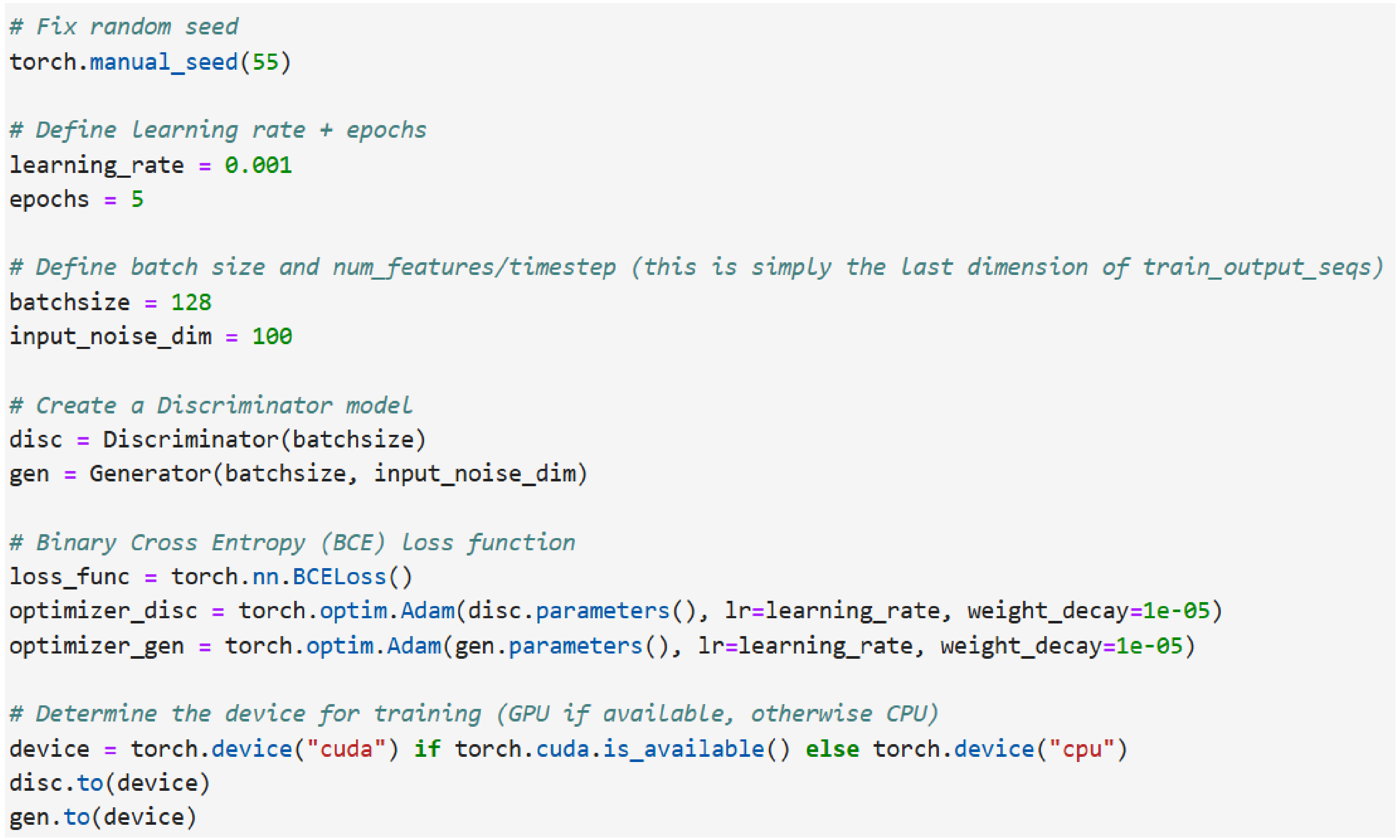
Takes batchsize as inputs

Define FC1, FC2 layers
Uses LeakyReLU() as hidden layer activation
Uses sigmoid() as output layer activation

Define signal propagation
input image -> FC1 -> FC2 -> (0/1)

Use .squeeze() to reduce output to 0/1

Define Hyperparameters



```
# Fix random seed
torch.manual_seed(55)

# Define learning rate + epochs
learning_rate = 0.001
epochs = 5

# Define batch size and num_features/timestep (this is simply the last dimension of train_output_seqs)
batchsize = 128
input_noise_dim = 100

# Create a Discriminator model
disc = Discriminator(batchsize)
gen = Generator(batchsize, input_noise_dim)

# Binary Cross Entropy (BCE) loss function
loss_func = torch.nn.BCELoss()
optimizer_disc = torch.optim.Adam(disc.parameters(), lr=learning_rate, weight_decay=1e-05)
optimizer_gen = torch.optim.Adam(gen.parameters(), lr=learning_rate, weight_decay=1e-05)

# Determine the device for training (GPU if available, otherwise CPU)
device = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
disc.to(device)
gen.to(device)
```

Define learning rate and epoch number

Define batchsize and input noise dimensions

Define Discriminator and Generator networks

Using Binary Cross-Entropy loss and Adam Optimizer with L2 regularization

Device for training (GPU/CPU)

Identify Tracked Values

```
gen_train_loss_list = []
disc_train_loss_list = []
```

Lists for storing
generator/discriminator training loss

Train Model

```python
# Create DataLoader objects to efficiently load the training and test data in batches
train_loader = DataLoader(train_data, batch_size=batchsize, shuffle=False, drop_last=True)
```

Define the data loader for training and testing

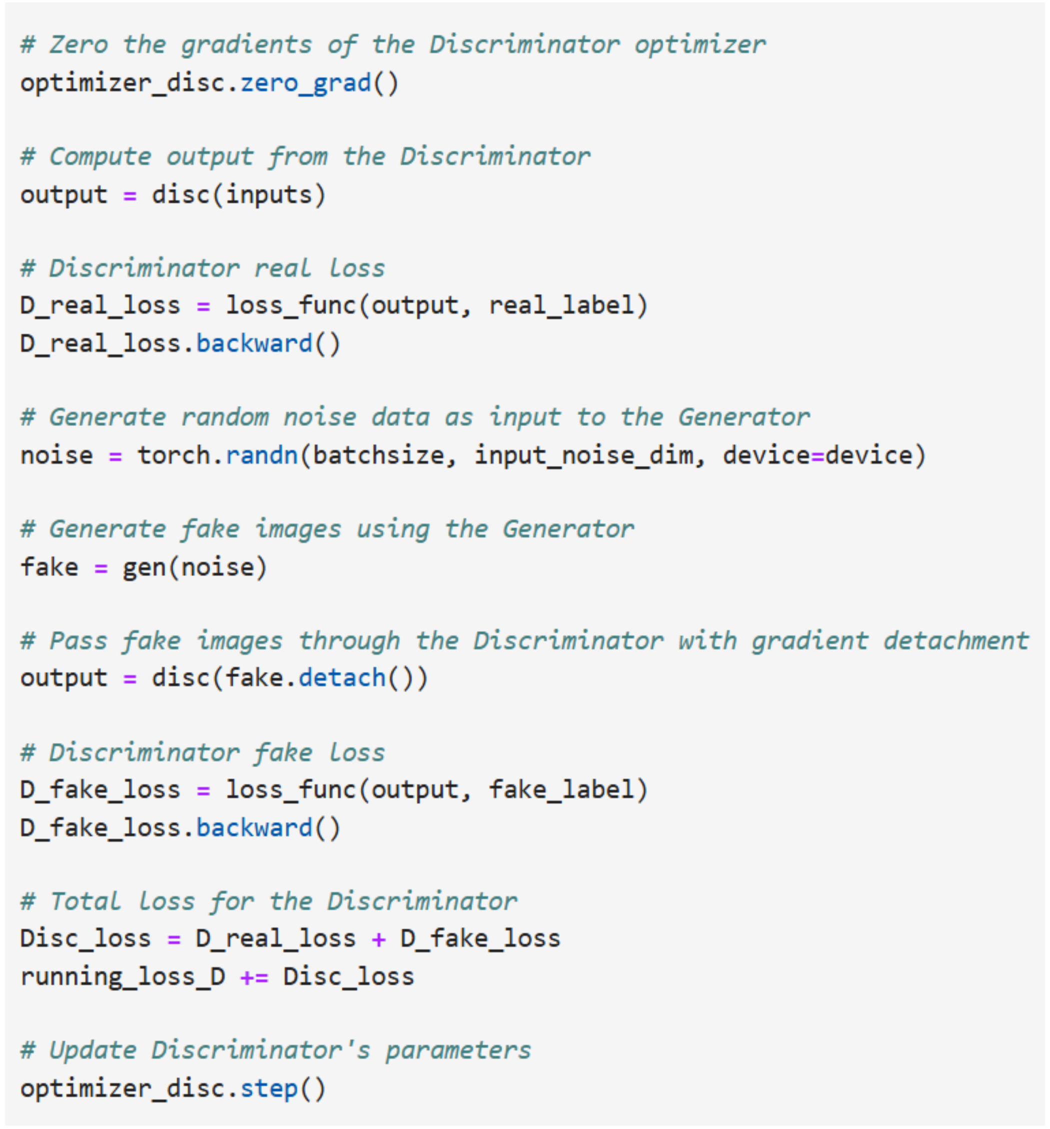
```python
# Set the device as CUDA or CPU based on availability
if torch.cuda.is_available():
    device = torch.device("cuda")
else:
    torch.device("cpu")

# Run training for each epoch
for epoch in range(epochs):

    print('Epoch {}/{}'.format(epoch + 1, epochs))
    running_loss_D = 0
    running_loss_G = 0

    for inputs, labels in train_loader:

        inputs = inputs.to(device)

        # Convert labels into torch tensors with the proper size as per the batch size
        real_label = torch.full((batchsize,), 1, dtype=inputs.dtype, device=device)
        fake_label = torch.full((batchsize,), 0, dtype=inputs.dtype, device=device)
```

Define device for training

Initialize Discriminator/Generator loss for given epoch

Create labels for real (1) vs fake (0) data

Train Model (Discriminator)



```
# Zero the gradients of the Discriminator optimizer
optimizer_disc.zero_grad()

# Compute output from the Discriminator
output = disc(inputs)

# Discriminator real loss
D_real_loss = loss_func(output, real_label)
D_real_loss.backward()

# Generate random noise data as input to the Generator
noise = torch.randn(batchsize, input_noise_dim, device=device)

# Generate fake images using the Generator
fake = gen(noise)

# Pass fake images through the Discriminator with gradient detachment
output = disc(fake.detach())

# Discriminator fake loss
D_fake_loss = loss_func(output, fake_label)
D_fake_loss.backward()

# Total loss for the Discriminator
Disc_loss = D_real_loss + D_fake_loss
running_loss_D += Disc_loss

# Update Discriminator's parameters
optimizer_disc.step()
```

Clear the gradient for discriminator network

Compute the discriminator outputs for given real data inputs

Compute the loss with respect to real labels (1)
Perform back propagation

Initialize noise to be fed into generator network

Compute the fake images from the generator

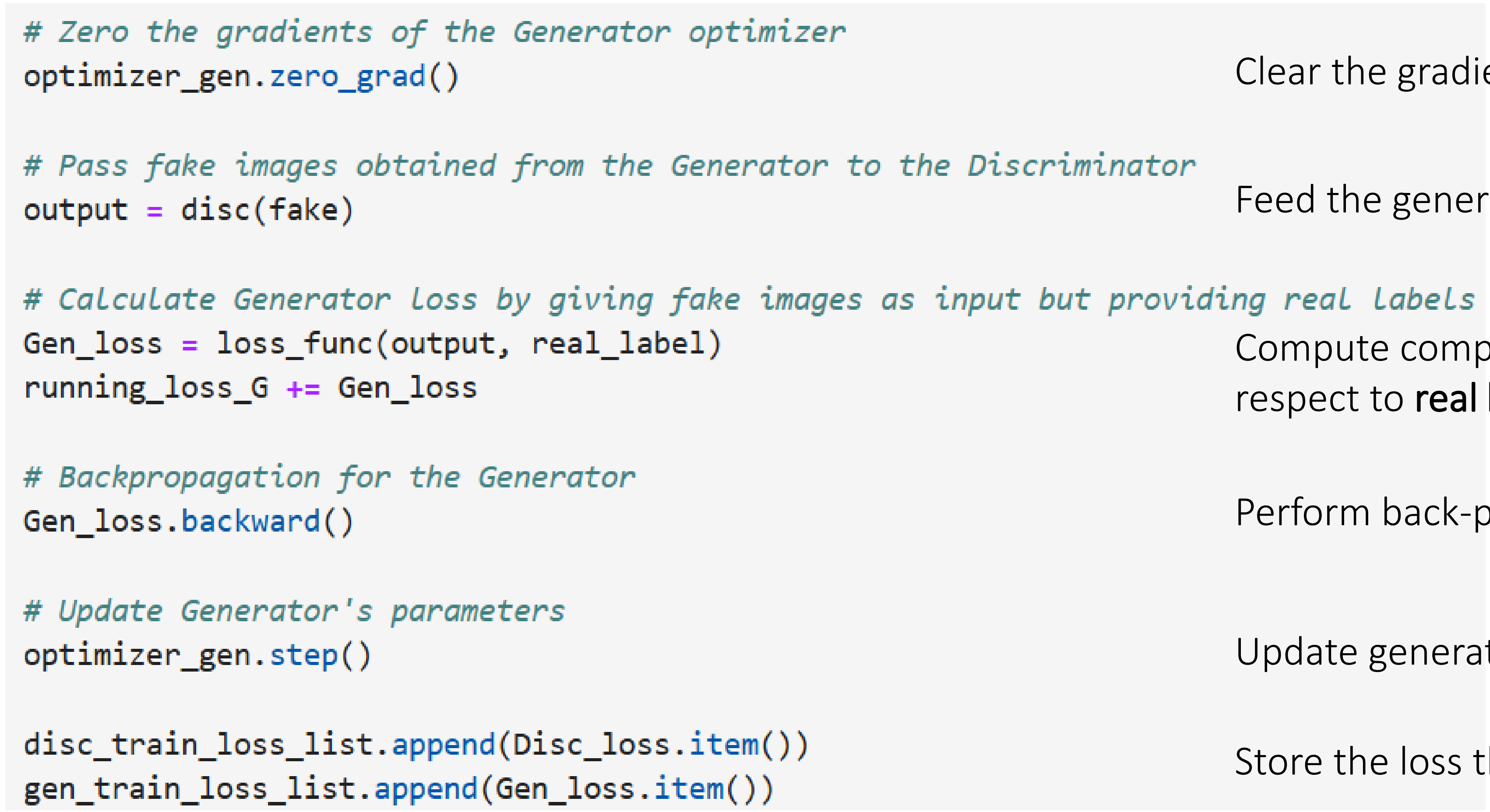
Feed the generated images to discriminator and get discriminator outputs

Compute the loss with respect to fake labels (0)
Perform back propagation

Final discriminator loss is **loss from real labels + fake labels**

Update discriminator network

Train Model (Generator)



```
# Zero the gradients of the Generator optimizer
optimizer_gen.zero_grad()

# Pass fake images obtained from the Generator to the Discriminator
output = disc(fake)

# Calculate Generator loss by giving fake images as input but providing real labels
Gen_loss = loss_func(output, real_label)
running_loss_G += Gen_loss

# Backpropagation for the Generator
Gen_loss.backward()

# Update Generator's parameters
optimizer_gen.step()

disc_train_loss_list.append(Disc_loss.item())
gen_train_loss_list.append(Gen_loss.item())
```

Clear the gradient for generator network

Feed the generated image to discriminator

Compute complementary discriminator loss with respect to **real labels**

Perform back-propagation

Update generator network

Store the loss the respective lists

Visualize & Evaluate Model

```
import matplotlib.pyplot as plt

# Function to plot an image
def show_image(img):
    # Convert the image from a tensor to a NumPy array
    npimg = img.numpy()
    # Transpose the NumPy array to the correct format for displaying
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
```

Define the function for converting torch image array to numpy array for plotting

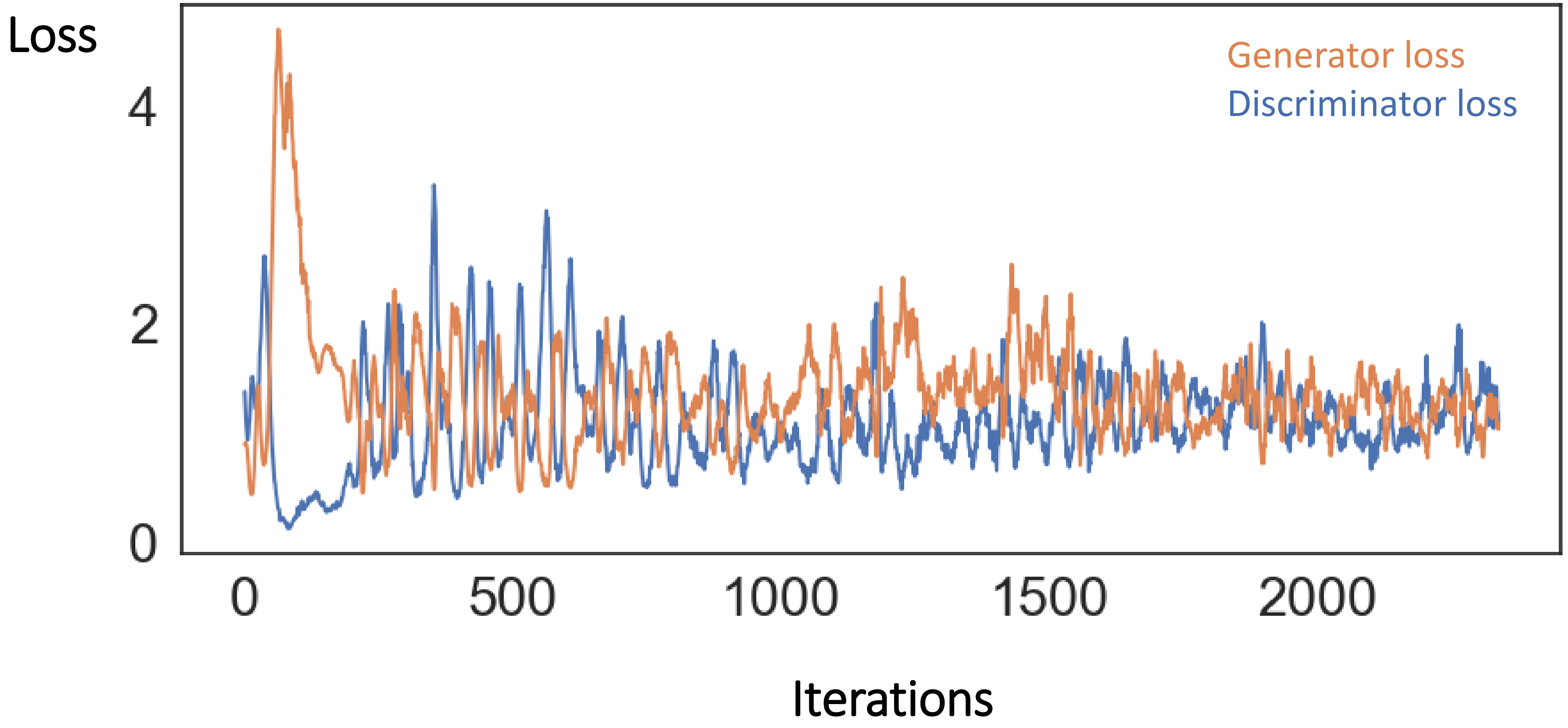
```
import torchvision

# Generate random noise for generating fake images
random_noise = torch.randn(128, input_noise_dim, device=device)

# Generate fake images from the random noise using the Generator
fake = gen(random_noise)
fake = fake.cpu()  # Move the generated fake images to the CPU for displaying

# Create a Matplotlib figure and axis for displaying the fake images
fig, ax = plt.subplots(figsize=(20, 8.5))

# Display the fake images in a grid (e.g., 10x5 grid)
show_image(torchvision.utils.make_grid(fake[0:50], 10, 5))

plt.show()
```

Define the random noise to be fed to generator for testing purpose

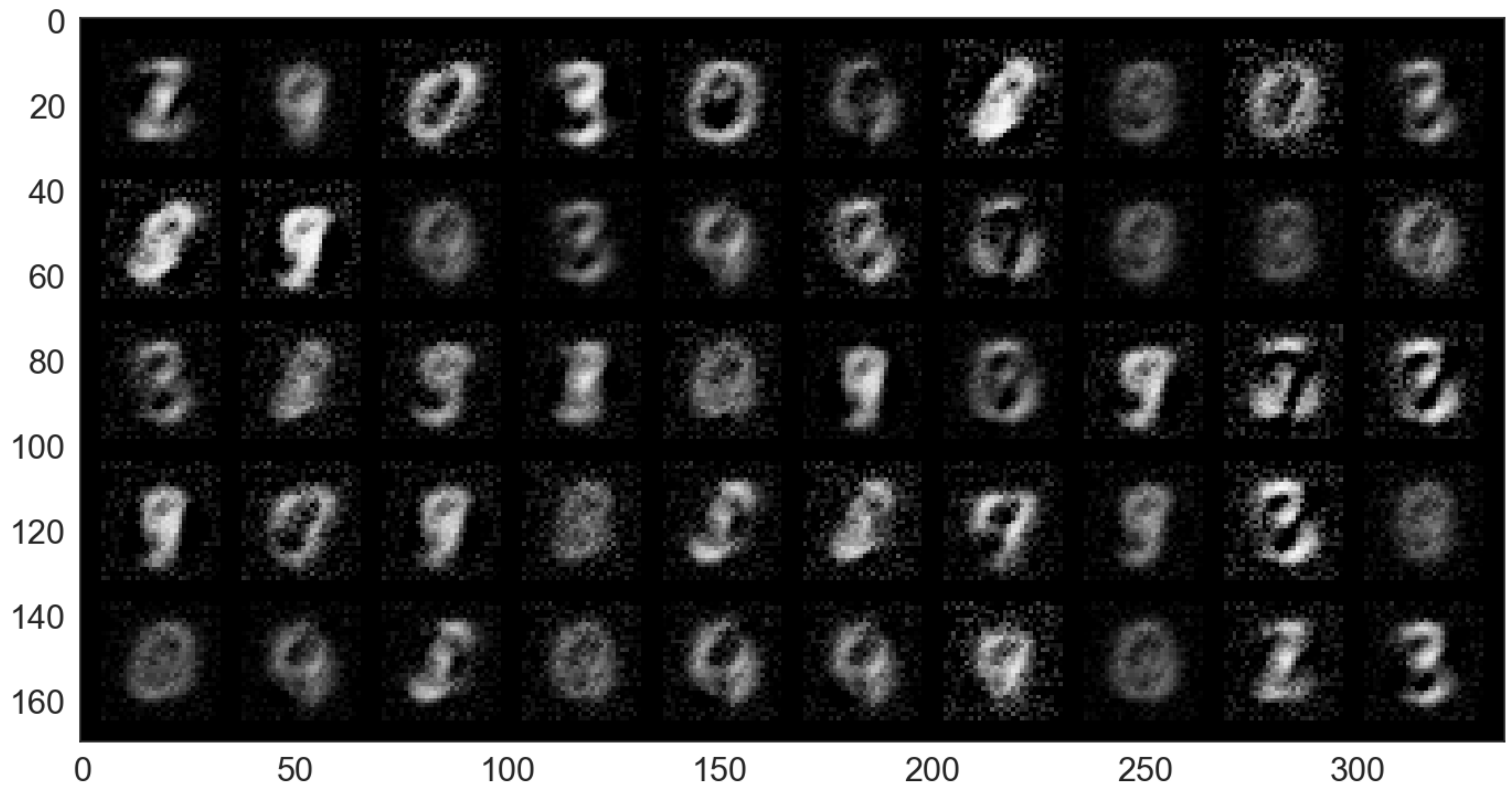
Feed the noise the generator to produce outputs and move them to cpu

Plot the first 50 generated images

Visualize & Evaluate Model



Visualize & Evaluate Model

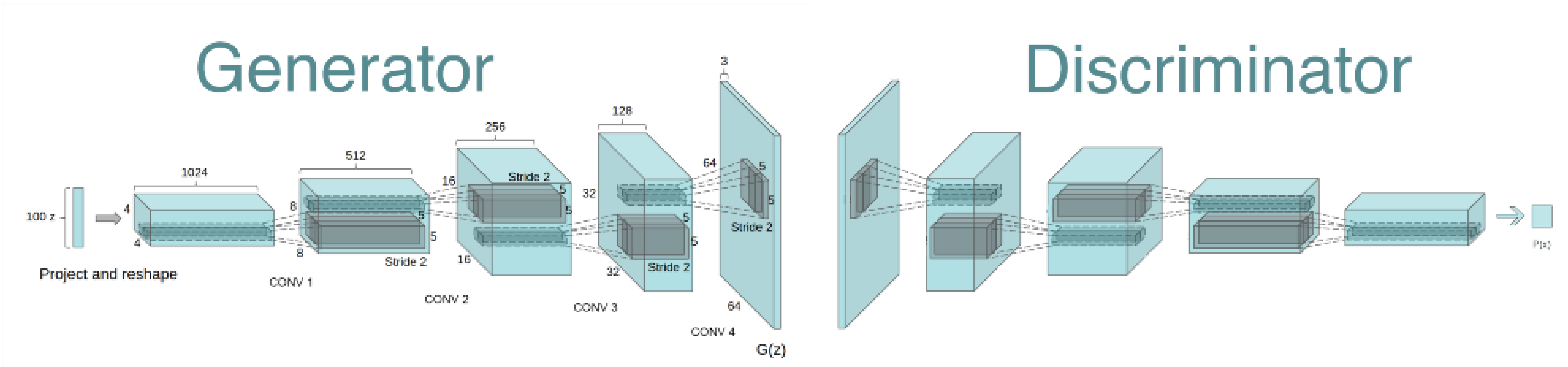


Generated samples

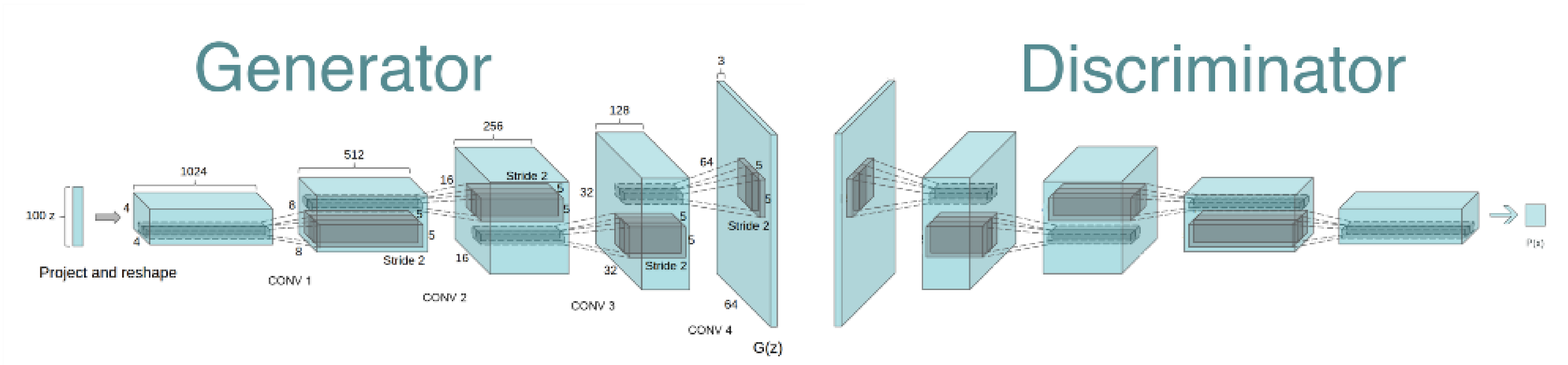
Generator Extension with Convolution:

2D Transpose Convolution

DCGAN Architecture



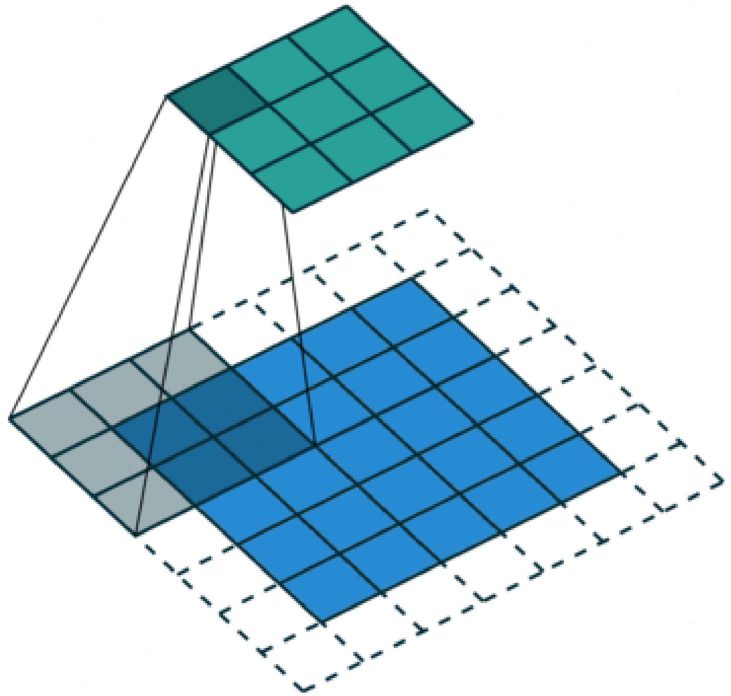
DCGAN Architecture



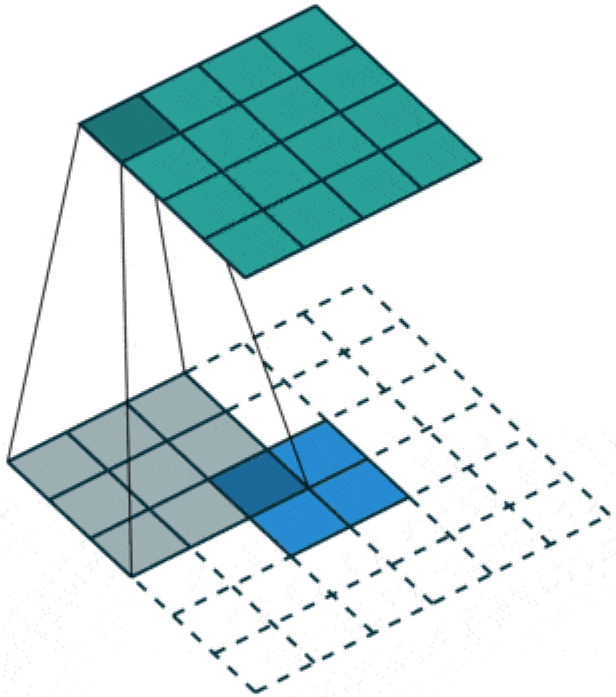
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
   ConvTranspose2d-1            [-1, 512, 4, 4]         819,200
       BatchNorm2d-2            [-1, 512, 4, 4]           1,024
              ReLU-3            [-1, 512, 4, 4]               0
   ConvTranspose2d-4            [-1, 256, 8, 8]       2,097,152
       BatchNorm2d-5            [-1, 256, 8, 8]             512
              ReLU-6            [-1, 256, 8, 8]               0
   ConvTranspose2d-7          [-1, 128, 16, 16]         524,288
       BatchNorm2d-8          [-1, 128, 16, 16]             256
              ReLU-9          [-1, 128, 16, 16]               0
  ConvTranspose2d-10           [-1, 64, 32, 32]         131,072
      BatchNorm2d-11           [-1, 64, 32, 32]             128
             ReLU-12           [-1, 64, 32, 32]               0
  ConvTranspose2d-13            [-1, 3, 64, 64]           3,072
             Tanh-14            [-1, 3, 64, 64]               0
----------------------------------------------------------------
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 32, 32]           3,072
         LeakyReLU-2           [-1, 64, 32, 32]               0
            Conv2d-3          [-1, 128, 16, 16]         131,072
       BatchNorm2d-4          [-1, 128, 16, 16]             256
         LeakyReLU-5          [-1, 128, 16, 16]               0
            Conv2d-6            [-1, 256, 8, 8]         524,288
       BatchNorm2d-7            [-1, 256, 8, 8]             512
         LeakyReLU-8            [-1, 256, 8, 8]               0
            Conv2d-9            [-1, 512, 4, 4]       2,097,152
      BatchNorm2d-10            [-1, 512, 4, 4]           1,024
        LeakyReLU-11            [-1, 512, 4, 4]               0
           Conv2d-12              [-1, 1, 1, 1]           8,192
          Sigmoid-13              [-1, 1, 1, 1]               0
          Flatten-14                    [-1, 1]               0
================================================================
```

Conv2D vs ConvTranspose2D

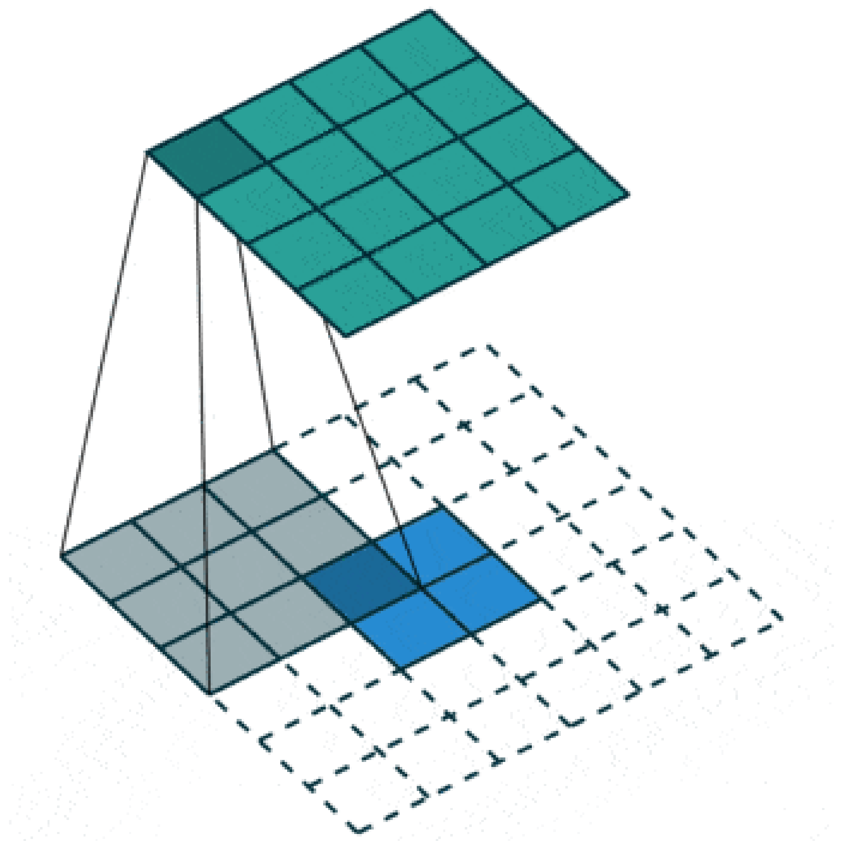


Conv2D()
input image = (5, 5)
Kernel size = (3, 3)
Output image = (3, 3)



ConvTranspose2D()
input image = (2, 2)
Kernel size = (3, 3)
Output image = (4, 4)

Conv2D vs ConvTranspose2D



torch.nn.ConvTranspose2d(

in_channels	# of channels of input
out_channels	# of channels of output
kernel_size	Size of the convolving Filter
stride	Stride of the convolution
Padding	Padding added to input

)

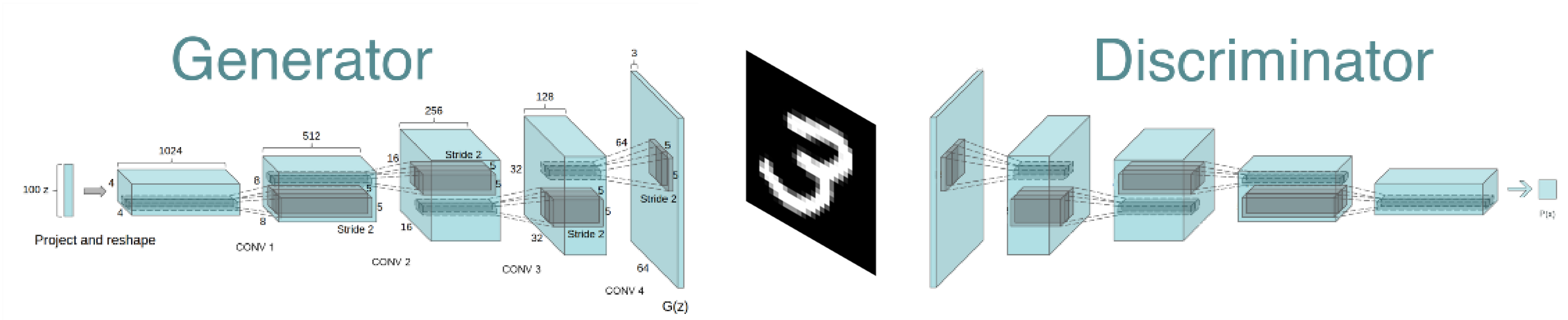
$$H\_out=(H\_in-1)*\text{stride}-2*\text{padding}+1*(\text{kernel\_size}-1)+1$$

$$W\_out=(W\_in-1)*\text{stride}-2*\text{padding}+1*(\text{kernel\_size}-1)+1$$

LAB 7 ASSIGNMENT:

MNIST Generation with DCGAN

MNIST Generation with DCGAN



In this exercise, you will use DCGAN architecture to generate **MNIST hand-written images.**

You are free to design architectures for Generator and Discriminator such as # of convolution layers, activation functions, regularization techniques etc.

You are also free to pick your own hyperparameters e.g., total epochs, batch size, learning rate, optimizer etc

Make sure to use **ConvTranspose2D()** for Generator instead of Conv2d().

After training, plot **training loss for both generator and discriminator** as well as the **50 best generated samples** similar to example task. Comment on how their qualities different from Vanilla-GAN - Are they better quality?