vanila_GAN

May 28, 2025

0.1 GAN

- data : MNIST

[ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F

from torchvision import datasets
from torchvision import transforms
from torch.utils.data import DataLoader

import matplotlib.pyplot as plt

# device setting for gpu users
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("device: ", device)
torch.backends.cudnn.enabled = False
```

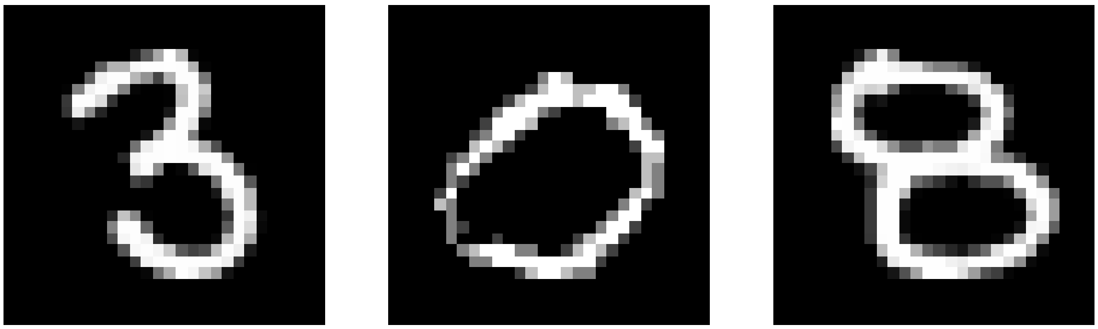
```
device:  cuda
```

0.1.1 2. DATA LOAD

[ ]:
```
epochs = 300
batch_size = 128
z_dim = 100

transform = transforms.Compose([transforms.ToTensor(), transforms.
  ↪Normalize(mean = (0.5, ),std=(0.5, ))])
mnist_dataset = datasets.MNIST(root = './data/', train = True,␣
  ↪transform=transform, download=True)
dataloader = DataLoader(mnist_dataset, batch_size = batch_size, shuffle=True,␣
  ↪drop_last=True)
```

[ ]:
```
#Random visualization      !
figure = plt.figure(figsize=(8,8))
cols, rows = 3,1
for i in range(1, cols*rows+1):
```

```
    #0    len         1    -> Tensor
    # .item()               int/float
    sample_idx = torch.randint(len(mnist_dataset), size=(1,)).item()
    img, label = mnist_dataset[sample_idx]
    figure.add_subplot(rows, cols, i)
    plt.axis("off") #hide x axis, y axis
    plt.imshow(img.squeeze(), cmap='gray')
plt.show()
```



0.1.2 3.Modeling

[ ]:
```
class Generator(nn.Module):
    def __init__(self, latent_dims, momentum=0.8):
        super(Generator, self).__init__()
        self.latent_dims = latent_dims

        self.fc1 = nn.Linear(latent_dims, 128)
        self.bn1 = nn.BatchNorm1d(128, momentum = momentum)

        self.fc2 = nn.Linear(128, 256)
        self.bn2 = nn.BatchNorm1d(256, momentum = momentum)

        self.fc3 = nn.Linear(256,512)
        self.bn3 = nn.BatchNorm1d(512, momentum = momentum)

        self.fc4 = nn.Linear(512, 1024)
        self.bn4 = nn.BatchNorm1d(1024, momentum = momentum)

        self.fc5 = nn.Linear(1024, 784)

        self.initialize()

    def initialize(self):
        #  xavier
```

```
        for m in self.modules():
            if isinstance(m, nn.Linear):
                nn.init.xavier_uniform_(m.weight)
                if m.bias is not None:
                    nn.init.zeros_(m.bias)

    def forward(self, z):
        #Relu -> leaky    !
        z = self.bn1(F.leaky_relu(self.fc1(z), negative_slope=0.2))
        z = self.bn2(F.leaky_relu(self.fc2(z), negative_slope=0.2))
        z = self.bn3(F.leaky_relu(self.fc3(z), negative_slope=0.2))
        z = self.bn4(F.leaky_relu(self.fc4(z), negative_slope=0.2))
        z = self.fc5(z)
        return z
```

[ ]:
```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.fc1 = nn.Linear(784, 256) #512
        self.fc2 = nn.Linear(256, 128)
        self.fc3 = nn.Linear(128, 1)

        self.initialize()

    def initialize(self):
        #  xavier
        for m in self.modules():
            if isinstance(m, nn.Linear):
                nn.init.xavier_uniform_(m.weight)
                if m.bias is not None:
                    nn.init.zeros_(m.bias)

    def forward(self, x):
        #ReLU -> leaky
        x = F.leaky_relu(self.fc1(x), negative_slope=0.2)
        x = F.leaky_relu(self.fc2(x), negative_slope=0.2)
        x = self.fc3(x)
        return torch.sigmoid(x)
```

[ ]:
```
generator = Generator(latent_dims = z_dim).to(device)
discriminator = Discriminator().to(device)
print("Generator :", generator)
print("Discriminator :",discriminator)
```

```
Generator : Generator(
  (fc1): Linear(in_features=100, out_features=128, bias=True)
  (bn1): BatchNorm1d(128, eps=1e-05, momentum=0.8, affine=True,
```

```
track_running_stats=True)
  (fc2): Linear(in_features=128, out_features=256, bias=True)
  (bn2): BatchNorm1d(256, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc3): Linear(in_features=256, out_features=512, bias=True)
  (bn3): BatchNorm1d(512, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc4): Linear(in_features=512, out_features=1024, bias=True)
  (bn4): BatchNorm1d(1024, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc5): Linear(in_features=1024, out_features=784, bias=True)
)
Discriminator : Discriminator(
  (fc1): Linear(in_features=784, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=128, bias=True)
  (fc3): Linear(in_features=128, out_features=1, bias=True)
)
```

0.1.3 4.train

[ ]:
```
def train_model(latent_dims, discriminator, generator,
                batch_size, dis_optimizer, gen_optimizer,
                criterion, dataloader, epochs, device):
    #
    testing_random_latent = torch.randn(5, latent_dims).to(device)

    #   loss
    dis_loss_list = []
    gen_loss_list = []

    for epoch in range(epochs):
        epoch_dis_loss = 0.0
        epoch_gen_loss = 0.0
        num_batches = 0

        #
        for batch_index, (batch_images, _) in enumerate(dataloader):
            num_batches += 1

            #      1, fake  0
            reals = torch.ones(batch_size, 1).to(device)
            fakes = torch.zeros(batch_size, 1).to(device)

            #   1
            batch_images = batch_images.view(batch_size, -1).to(device)

            ## DISCRIMINATOR   ##
```

```
        #Real Image    discrim
        dis_results = discriminator(batch_images)
        dis_real_loss = criterion(dis_results, reals) #1     loss

        #Fake Image
        latent = torch.randn(batch_size, latent_dims).to(device)
        fake_images = generator(latent).detach() #

        #fake image    discrim
        dis_results = discriminator(fake_images)
        dis_fake_loss = criterion(dis_results, fakes) #0     loss

        #discrim   loss
        dis_total_loss = dis_real_loss + dis_fake_loss

        #discrim param
        discriminator.zero_grad() #
        dis_total_loss.backward()
        dis_optimizer.step() #param

        ## Generator   ##
        #Fake Image
        latent = torch.randn(batch_size, latent_dims).to(device)
        fake_images = generator(latent)

        #fake image    discrim
        dis_results = discriminator(fake_images)

        #generator loss
        #fake  real      (1    )
        #-log(D(G(z)))
        ###   log(1-D(G(z)))      ,              .
        ###  -log(D(g(z)))     = log(D(g(z)))
        gen_loss = criterion(dis_results, reals) #

        #generator param
        generator.zero_grad()
        gen_loss.backward()
        gen_optimizer.step()

        #   epoch
        epoch_dis_loss += dis_total_loss.item()
        epoch_gen_loss += gen_loss.item()

    #   epoch   loss
    dis_loss_list.append(epoch_dis_loss / num_batches)
    gen_loss_list.append(epoch_gen_loss / num_batches)
```

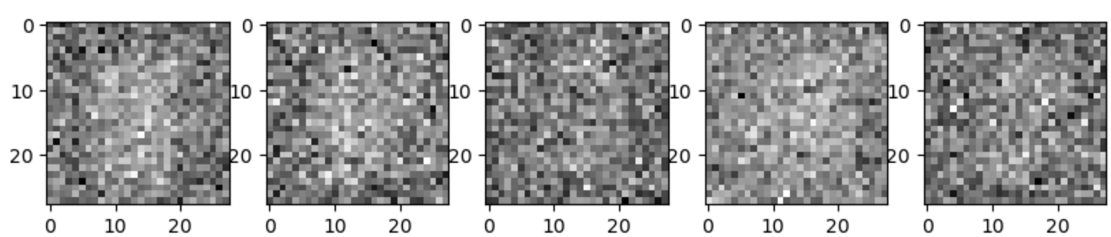
```
        if epoch % 20 == 0:
            print(f"EPOCH {epoch}: Discriminator Loss: {dis_loss_list[-1]:.4f},␣
↪Generator Loss: {gen_loss_list[-1]:.4f}")

            with torch.no_grad():
                #      test image
                testing_fake_images = generator(testing_random_latent)
                testing_fake_images = testing_fake_images.reshape(5, 28, 28).
↪cpu().detach().numpy() #1.Numpy        cpu    !

                #Visualization
                plt.figure(figsize=(10,5))
                plt.title("GENERATED IMAGE, EPOCH {}".format(epoch))
                for i in range(5):
                    plt.subplot(1, 5, int(i) + 1)
                    plt.imshow(testing_fake_images[i], cmap='gray')
                plt.show()

    return discriminator, generator, dis_loss_list, gen_loss_list
```

[ ]:
```
criterion = nn.BCELoss()
generator_optim = torch.optim.Adam(generator.parameters(), lr = 0.002, betas =␣
 ↪(0.5, 0.999))
discriminator_optim = torch.optim.Adam(discriminator.parameters(), lr=0.002,␣
 ↪betas = (0.5, 0.999))
```

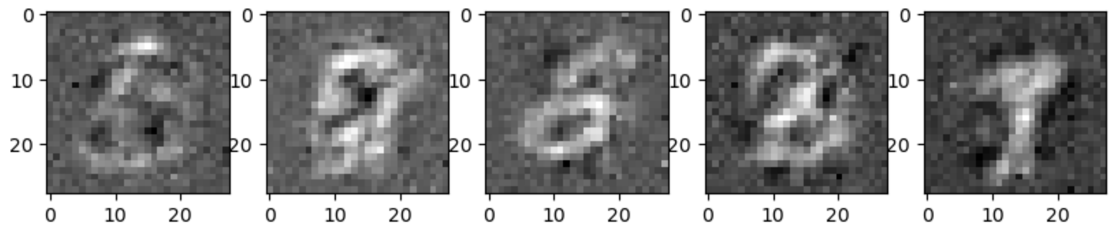
[ ]:
```
#  (1),  (0)       .
discriminator, generator, dis_losses, gen_losses = train_model(z_dim,␣
 ↪discriminator, generator, batch_size, discriminator_optim, generator_optim,␣
 ↪criterion, dataloader, epochs, device)
```

```
EPOCH 0: Discriminator Loss: 1.3546, Generator Loss: 1.3886
```

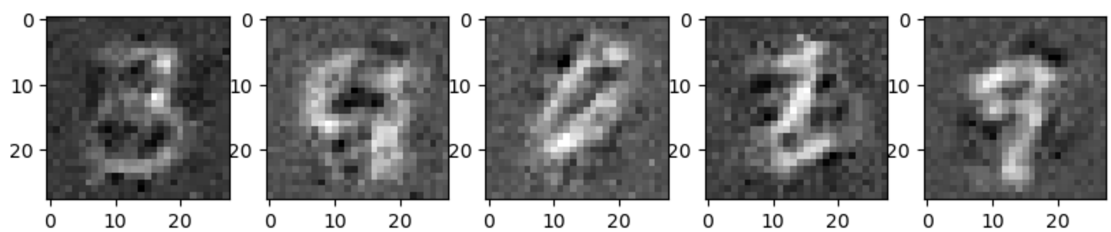
```
/tmp/ipykernel_55875/3051221125.py:89: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be removed two
minor releases later; explicitly call ax.remove() as needed.
  plt.subplot(1, 5, int(i) + 1)
```



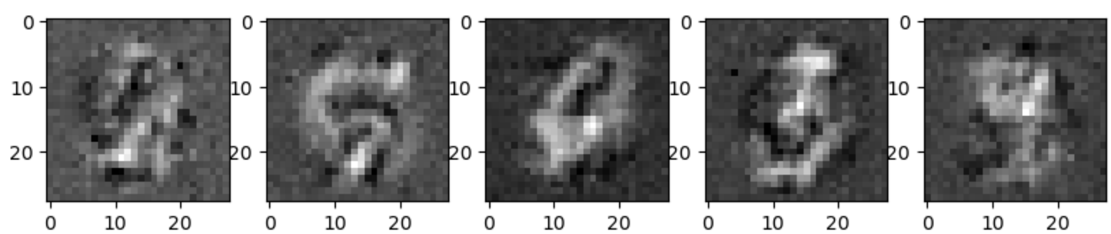
EPOCH 20: Discriminator Loss: 1.0016, Generator Loss: 1.9714



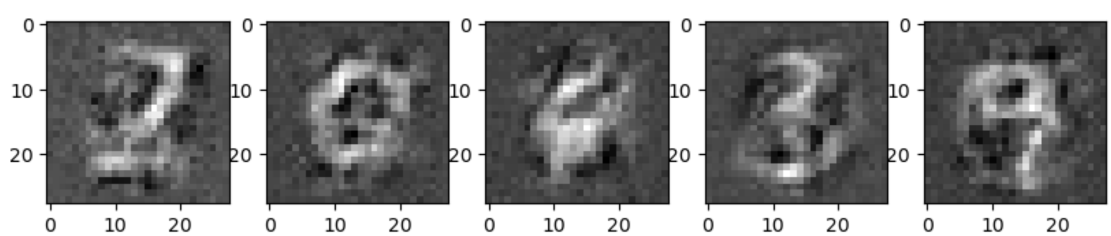
EPOCH 40: Discriminator Loss: 1.0224, Generator Loss: 2.0564



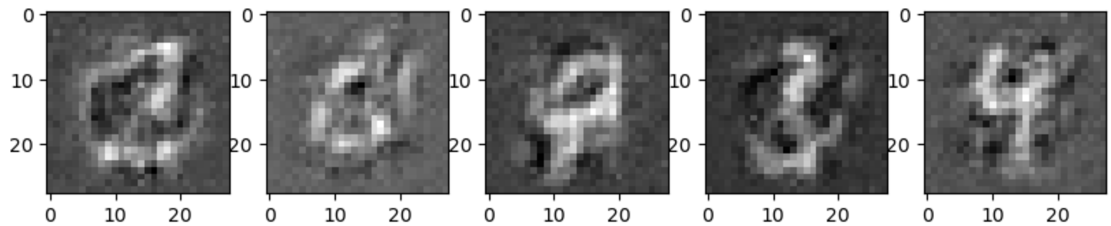
EPOCH 60: Discriminator Loss: 1.0295, Generator Loss: 2.2307



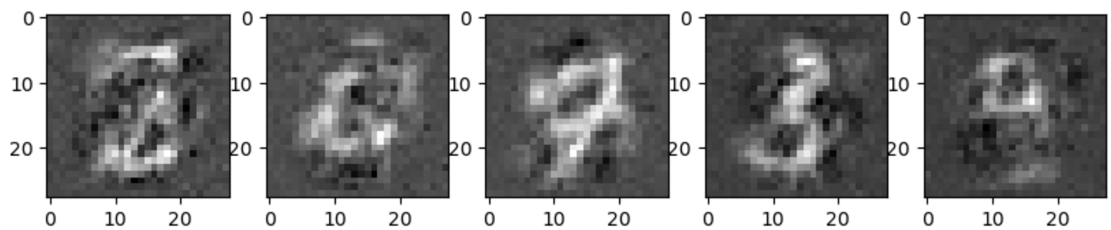
EPOCH 80: Discriminator Loss: 1.0016, Generator Loss: 2.2760



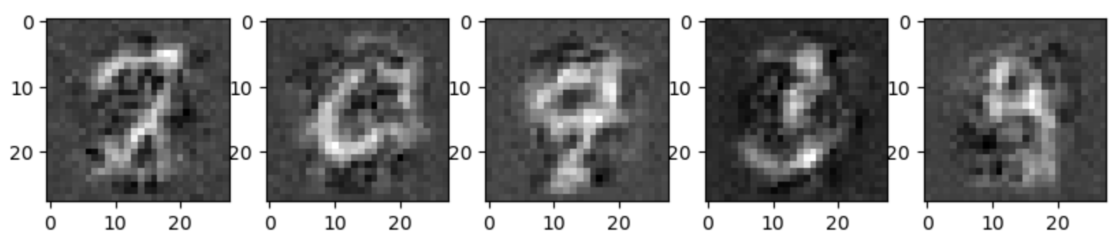
EPOCH 100: Discriminator Loss: 0.9628, Generator Loss: 2.4511



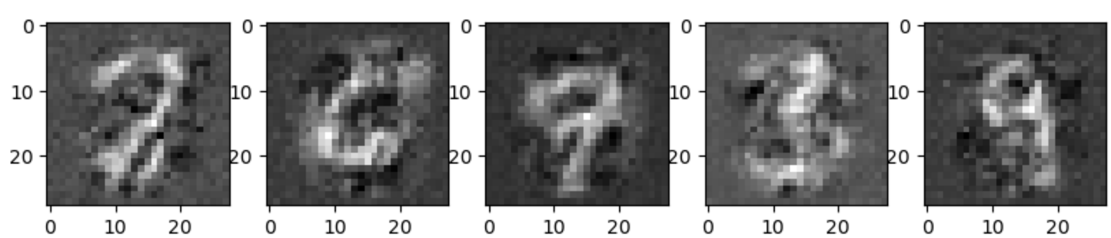
EPOCH 120: Discriminator Loss: 0.9969, Generator Loss: 2.4834



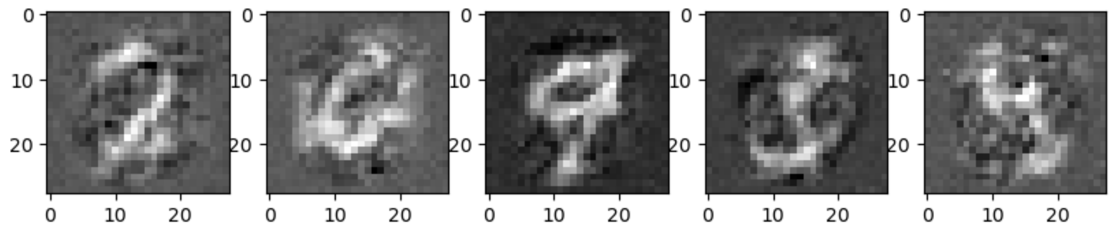
EPOCH 140: Discriminator Loss: 1.0104, Generator Loss: 2.5731



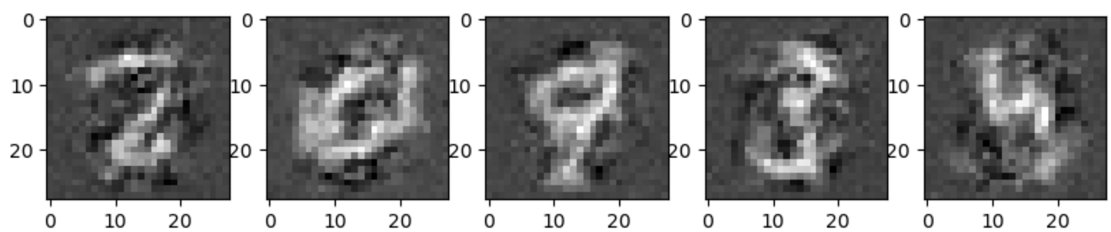
EPOCH 160: Discriminator Loss: 0.9880, Generator Loss: 2.7584



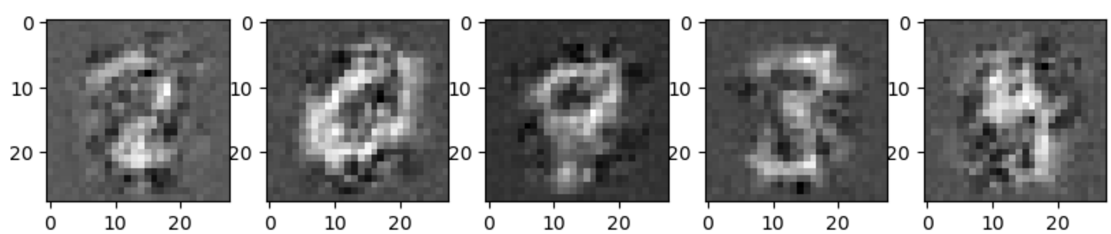
EPOCH 180: Discriminator Loss: 0.9616, Generator Loss: 2.7708



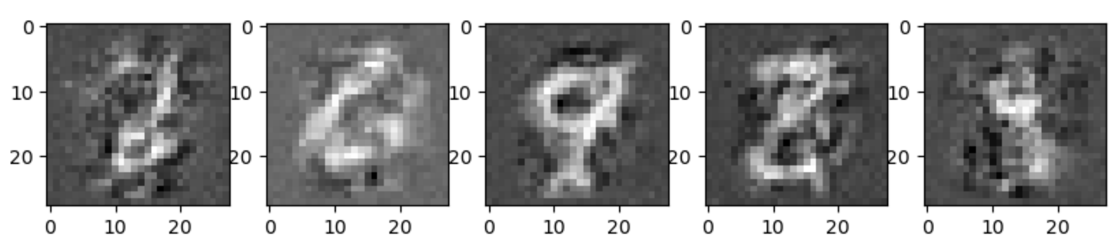
EPOCH 200: Discriminator Loss: 0.8876, Generator Loss: 2.8733



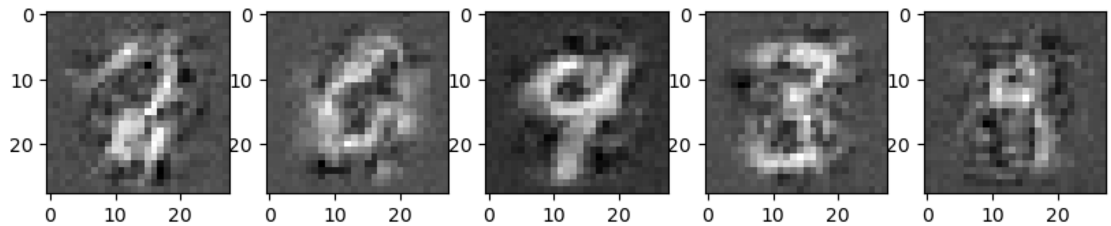
EPOCH 220: Discriminator Loss: 0.9919, Generator Loss: 2.7534



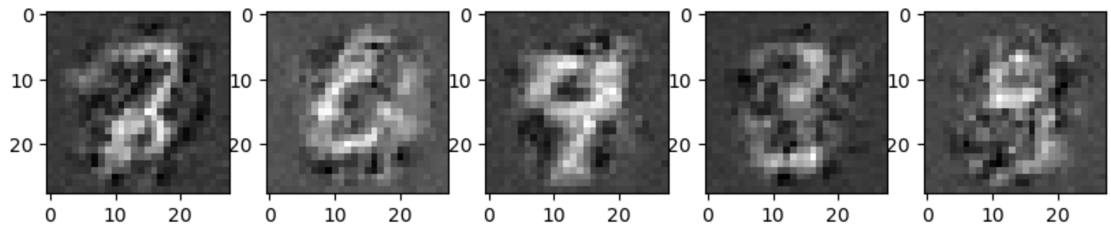
EPOCH 240: Discriminator Loss: 0.8932, Generator Loss: 2.9371



EPOCH 260: Discriminator Loss: 0.8667, Generator Loss: 3.0562

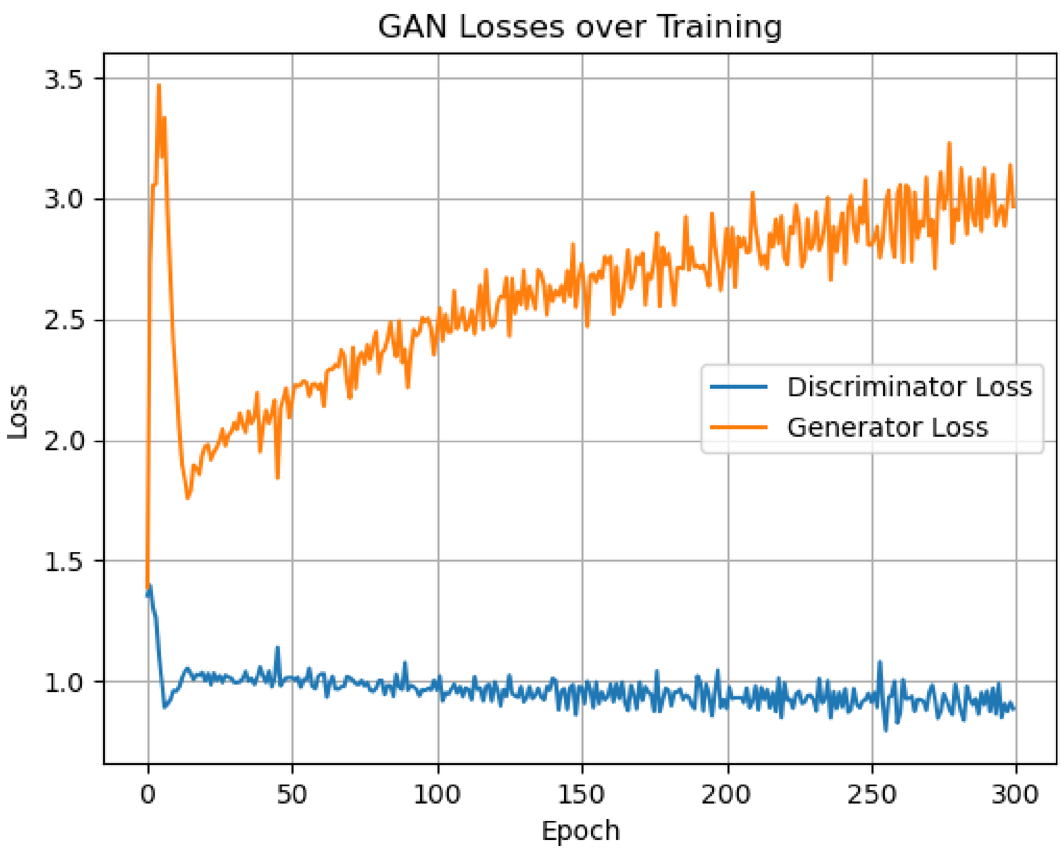


EPOCH 280: Discriminator Loss: 0.9228, Generator Loss: 2.9109



[ ]:
```
torch.save(generator.state_dict(), 'G.ckpt')
torch.save(discriminator.state_dict(), 'D.ckpt')
```

[ ]:
```
# Loss
import matplotlib.pyplot as plt
plt.plot(dis_losses, label="Discriminator Loss")
plt.plot(gen_losses, label="Generator Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("GAN Losses over Training")
plt.legend()
plt.grid(True)
plt.show()
```



0.1.4 5.Evaluation

[ ]:
```
G = Generator(latent_dims=z_dim).to(device)
G.load_state_dict(torch.load("G.ckpt", map_location=device))
G.eval()  #
```

```
/tmp/ipykernel_55875/4011423156.py:2: FutureWarning: You are using `torch.load`
with `weights_only=False` (the current default value), which uses the default
pickle module implicitly. It is possible to construct malicious pickle data
which will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  G.load_state_dict(torch.load("G.ckpt", map_location=device))
```

[ ]:
```
Generator(
  (fc1): Linear(in_features=100, out_features=128, bias=True)
  (bn1): BatchNorm1d(128, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc2): Linear(in_features=128, out_features=256, bias=True)
  (bn2): BatchNorm1d(256, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc3): Linear(in_features=256, out_features=512, bias=True)
  (bn3): BatchNorm1d(512, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc4): Linear(in_features=512, out_features=1024, bias=True)
  (bn4): BatchNorm1d(1024, eps=1e-05, momentum=0.8, affine=True,
track_running_stats=True)
  (fc5): Linear(in_features=1024, out_features=784, bias=True)
)
```

[ ]:
```
# 100  latent     (    =100)
z = torch.randn(100, 100).to(device)  # [batch_size, z_dim]

with torch.no_grad():
    fake_images = G(z)  # shape: [100, 1, 28, 28]
```

[ ]:
```
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.imshow(fake_images[i].cpu().reshape(28, 28), cmap='gray')
    plt.axis('off')
plt.tight_layout()
plt.show()
```