PDF_Code

September 16, 2022

1 Imports

[ ]:
```
import torch
import torch.nn as nn
from torchvision import datasets
import torchvision.transforms as tf
from torch.utils.data import DataLoader
import matplotlib.animation as animate
import matplotlib.pyplot as plt
import numpy as np
import torchvision.datasets
import random
```

2 Question 3

2.1 Create dataset/loader and create the random seed

[ ]:
```
# seed = 393 # for same results
seed = random.randint(1, 10000) # for variation
print("Random Seed: ", seed)
random.seed(seed)
torch.manual_seed(seed)

img_size = 64
batch_size = 128
workers = 4
root="./data/CelebA"
nz = 100
# Size of feature maps in generator
gen_features = 64
# Size of feature maps in discriminator
disc_features = 64
# Number of training epochs
num_epochs = 1
# Learning rate for optimizers
D_lr = 0.002
G_lr = 0.001
```

```
dataset = datasets.ImageFolder(root=root,
                           transform=tf.Compose([
                               tf.Resize(img_size),
                               tf.CenterCrop(img_size),
                               tf.ToTensor(),
                               tf.Normalize(mean=(0.50612009, 0.42543493, 0.
↪38282761), std=(0.26589054, 0.24521921, 0.24127836)),
                           ]))

dataloader = torch.utils.data.DataLoader(dataset, batch_size=batch_size,␣
↪shuffle=True, num_workers=workers)

DEVICE = 'mps' if torch.backends.mps.is_available() else 'cuda' if torch.cuda.
↪is_available() else 'cpu'

# Plot some training images
real_batch = next(iter(dataloader))
plt.figure(figsize=(8,8))
plt.axis("off")
plt.title("Training Images")
grid_img = torchvision.utils.make_grid(real_batch[0])
plt.imshow(np.transpose(torchvision.utils.make_grid(real_batch[0][:64],␣
↪padding=5, normalize=True).cpu(),(1,2,0)))
```

```
Random Seed:  4120
```

[ ]:

```
<matplotlib.image.AxesImage at 0x1482bdc10>
```

Training Images

2.2 Setup weight function

[ ]:
```
def weights_init(m):
    classname = m.__class__.__name__
    if classname.find('Conv') != -1:
        nn.init.normal_(m.weight.data, 0.0, 0.02)
    elif classname.find('BatchNorm') != -1:
        nn.init.normal_(m.weight.data, 1.0, 0.02)
        nn.init.constant_(m.bias.data, 0)
```

2.3 Generator Setup and Initialization

[ ]:
```
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.gen = nn.Sequential(
            # N x nz x 1 x 1
            nn.ConvTranspose2d(in_channels=nz, out_channels=gen_features * 8, kernel_size=4, stride=1, padding=0, bias=False),
            nn.BatchNorm2d(gen_features * 8),
            nn.Dropout(),
            nn.ReLU(True),
            # N x (gen_features*8) x 4 x 4
            # Paper uses kernel_size=5, stride=2 ==> cannot get 8x8 output
            nn.ConvTranspose2d(in_channels=gen_features * 8, out_channels=gen_features * 4, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(gen_features * 4),
            # nn.Dropout(),
            nn.ReLU(True),
            # N x (gen_features*4) x 8 x 8
            nn.ConvTranspose2d(in_channels=gen_features * 4, out_channels=gen_features * 2, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(gen_features * 2),
            # nn.Dropout(),
            nn.ReLU(True),
            # N x (gen_features*2) x 16 x 16
            nn.ConvTranspose2d(in_channels=gen_features * 2, out_channels=gen_features, kernel_size=4, stride=2, padding=1, bias=False),
            nn.BatchNorm2d(gen_features),
            nn.ReLU(True),
            # N x gen_features x 32 x 32
            nn.ConvTranspose2d(in_channels=gen_features, out_channels=3, kernel_size=4, stride=2, padding=1, bias=False),
            nn.Tanh()
            # N x 3 x 64 x 64
        )

    def forward(self, x):
        return self.gen(x)
```

[ ]:
```
# Create the generator
netG = Generator().to(DEVICE)

netG.apply(weights_init)
```

```
print(netG)
```

```
Generator(
  (gen): Sequential(
    (0): ConvTranspose2d(100, 512, kernel_size=(4, 4), stride=(1, 1),
bias=False)
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): ReLU(inplace=True)
    (4): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2),
padding=(1, 1), bias=False)
    (5): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (6): ReLU(inplace=True)
    (7): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2),
padding=(1, 1), bias=False)
    (8): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (9): ReLU(inplace=True)
    (10): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2),
padding=(1, 1), bias=False)
    (11): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (12): ReLU(inplace=True)
    (13): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1,
1), bias=False)
    (14): Tanh()
  )
)
```

2.4 Discriminator setup and initialization

```
[ ]: class Discriminator(nn.Module):
         def __init__(self):
             super(Discriminator, self).__init__()
             self.net = nn.Sequential(
                 # Nx3x64x64
                 nn.Conv2d(in_channels=3, out_channels=disc_features, kernel_size=4,␣
       ↪stride=2, padding=1, bias=False),
                 nn.LeakyReLU(0.1),
                 # N x disc_features x 32 x 32
                 self._step(in_channels=disc_features, out_channels=disc_features *␣
       ↪2, kernel_size=4, stride=2, padding=1),
                 # N x (disc_features*2) x 16 x 16
                 self._step(in_channels=disc_features * 2,␣
       ↪out_channels=disc_features * 4, kernel_size=4, stride=2, padding=1),
```

```
            self._step(in_channels=disc_features * 4,␣
↪out_channels=disc_features * 8, kernel_size=4, stride=2, padding=1),
            # N x (disc_features*8) x 4 x 4
            nn.Conv2d(in_channels=disc_features * 8, out_channels=1,␣
↪kernel_size=4, stride=1, padding=0),
            nn.Sigmoid()
            # N x 1 x 1 x 1
        )

    def _step(self, in_channels, out_channels, kernel_size, stride, padding):
        return nn.Sequential(
            nn.Conv2d(in_channels=in_channels, out_channels=out_channels,␣
↪kernel_size=kernel_size, stride=stride, padding=padding, bias=False),
            nn.BatchNorm2d(out_channels),
            nn.Dropout(),
            nn.LeakyReLU(0.1, inplace=True)
        )

    def forward(self, x):
        return self.net(x)
```

[ ]:
```
# Create the Discriminator
netD = Discriminator().to(DEVICE)

netD.apply(weights_init)

print(netD)
```

```
Discriminator(
  (net): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1),
bias=False)
    (1): LeakyReLU(negative_slope=0.1)
    (2): Sequential(
      (0): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1),
bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): Dropout(p=0.5, inplace=False)
      (3): LeakyReLU(negative_slope=0.1, inplace=True)
    )
    (3): Sequential(
      (0): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1),
bias=False)
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): Dropout(p=0.5, inplace=False)
```

```
      (3): LeakyReLU(negative_slope=0.1, inplace=True)
    )
    (4): Sequential(
      (0): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1),
bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): Dropout(p=0.5, inplace=False)
      (3): LeakyReLU(negative_slope=0.1, inplace=True)
    )
    (5): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1))
    (6): Sigmoid()
  )
)
```

2.5 Initialize Loss and Optimizers

[ ]:
```
criterion = nn.BCELoss()

# Create batch of latent vectors that we will use to visualize
#  the progression of the generator
fixed_noise = torch.randn(64, nz, 1, 1, device=DEVICE)

real_label = 1.
fake_label = 0.

# Setup Adam optimizer for D and G
optimizerD = torch.optim.Adam(netD.parameters(), lr=D_lr, betas=(0.5, 0.999))
optimizerG = torch.optim.Adam(netG.parameters(), lr=G_lr, betas=(0.5, 0.999))
```

2.6 Training Loop

[ ]:
```
# Lists to keep track of progress
img_list = []
G_losses = []
D_losses = []
iters = 0

print("Starting Training Loop...")
for epoch in range(num_epochs):
    for i, data in enumerate(dataloader, 0):
        ############################
        # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
        ###########################
        netD.zero_grad()
        real_cpu = data[0].to(DEVICE)
        b_size = real_cpu.size(0)
```

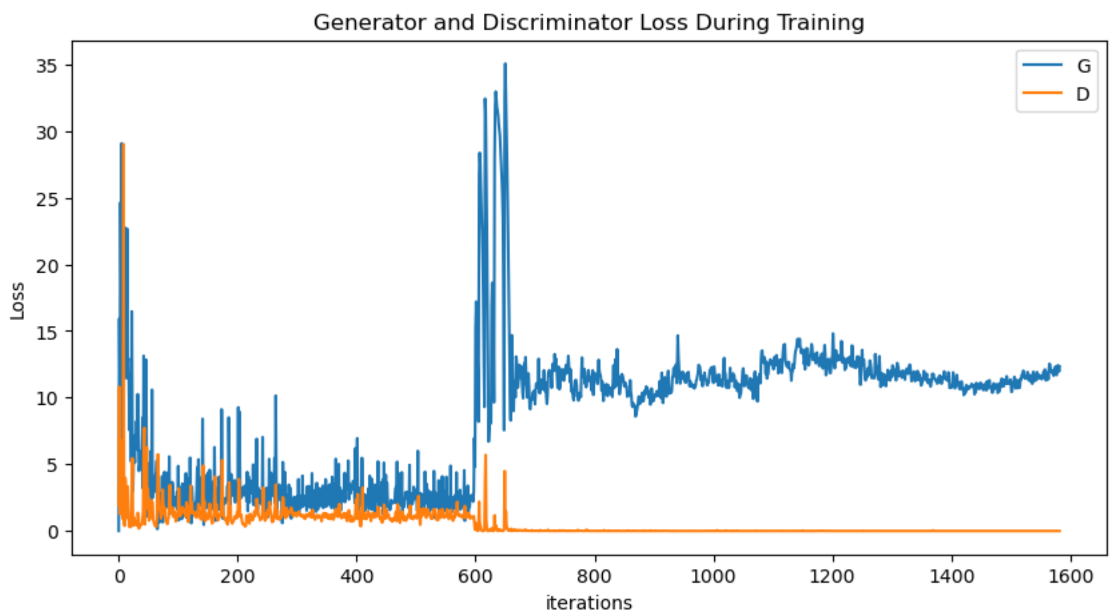
```
        label = torch.full((b_size,), real_label, dtype=torch.float, device=DEVICE)
        output = netD(real_cpu).view(-1)
        errD_real = criterion(output, label)
        errD_real.backward()
        D_x = output.mean().item()

        noise = torch.randn(b_size, nz, 1, 1, device=DEVICE)
        fake = netG(noise)
        label.fill_(fake_label)
        output = netD(fake.detach()).view(-1)
        errD_fake = criterion(output, label)
        errD_fake.backward()
        D_G_z1 = output.mean().item()
        lossD = errD_real + errD_fake
        optimizerD.step()

        ############################
        # (2) Update G network: maximize log(D(G(z)))
        ###########################
        netG.zero_grad()
        label.fill_(real_label)
        output = netD(fake).view(-1)
        lossG = criterion(output, label)
        lossG.backward()
        D_G_z2 = output.mean().item()
        optimizerG.step()

        if i % 50 == 0:
            print(f"[{epoch+1}/{num_epochs}][{i}/{len(dataloader)}] \tLoss_D: {lossD.item():.4f} \tLoss_G: {lossG.item():.4f} \tD(x): {D_x:.4f} \tD(G(z)): {D_G_z1:.4f}/{D_G_z2:.4f}")

        # save loss for plot
        G_losses.append(lossG.item())
        D_losses.append(lossD.item())

        # save G output on fixed noise
        if (iters % 500 == 0) or ((epoch == num_epochs-1) and (i == len(dataloader)-1)):
            with torch.no_grad():
                fake = netG(fixed_noise).detach().cpu()
            img_list.append(torchvision.utils.make_grid(fake, padding=2, normalize=True))

        iters += 1
```

```
Starting Training Loop…
[1/1][0/1583]   Loss_D: 1.9389  Loss_G: 0.0054  D(x): 0.3618    D(G(z)):
0.3226/0.9947
[1/1][50/1583]  Loss_D: 2.0078  Loss_G: 3.9719  D(x): 0.5728    D(G(z)):
0.1172/0.0670
[1/1][100/1583]         Loss_D: 1.7966  Loss_G: 4.8704  D(x): 0.8013    D(G(z)):
0.6483/0.0214
[1/1][150/1583]         Loss_D: 1.0107  Loss_G: 2.2443  D(x): 0.6656    D(G(z)):
0.3240/0.1722
[1/1][200/1583]         Loss_D: 1.0700  Loss_G: 2.7194  D(x): 0.5891    D(G(z)):
0.2161/0.1431
[1/1][250/1583]         Loss_D: 1.5566  Loss_G: 1.0166  D(x): 0.3323    D(G(z)):
0.1381/0.4231
[1/1][300/1583]         Loss_D: 1.2354  Loss_G: 2.6069  D(x): 0.6985    D(G(z)):
0.4324/0.1294
[1/1][350/1583]         Loss_D: 1.1985  Loss_G: 2.2526  D(x): 0.8029    D(G(z)):
0.4995/0.1717
[1/1][400/1583]         Loss_D: 0.9133  Loss_G: 1.5177  D(x): 0.7235    D(G(z)):
0.2819/0.2728
[1/1][450/1583]         Loss_D: 1.5814  Loss_G: 1.7351  D(x): 0.3210    D(G(z)):
0.1007/0.2439
[1/1][500/1583]         Loss_D: 1.0627  Loss_G: 2.7073  D(x): 0.6374    D(G(z)):
0.3274/0.1183
[1/1][550/1583]         Loss_D: 1.0872  Loss_G: 1.5815  D(x): 0.5579    D(G(z)):
0.2525/0.2495
[1/1][600/1583]         Loss_D: 0.6390  Loss_G: 15.2075         D(x): 0.9767
D(G(z)): 0.3870/0.0000
[1/1][650/1583]         Loss_D: 0.4340  Loss_G: 35.0539         D(x): 0.8366
D(G(z)): 0.0000/0.0000
[1/1][700/1583]         Loss_D: 0.0128  Loss_G: 9.5067  D(x): 0.9923    D(G(z)):
0.0029/0.0042
[1/1][750/1583]         Loss_D: 0.0139  Loss_G: 12.1537         D(x): 0.9966
D(G(z)): 0.0068/0.0043
[1/1][800/1583]         Loss_D: 0.0032  Loss_G: 11.5051         D(x): 0.9982
D(G(z)): 0.0011/0.0008
[1/1][850/1583]         Loss_D: 0.0004  Loss_G: 10.8497         D(x): 0.9999
D(G(z)): 0.0003/0.0003
[1/1][900/1583]         Loss_D: 0.0012  Loss_G: 10.0326         D(x): 0.9999
D(G(z)): 0.0011/0.0020
[1/1][950/1583]         Loss_D: 0.0005  Loss_G: 11.6630         D(x): 0.9999
D(G(z)): 0.0003/0.0010
[1/1][1000/1583]        Loss_D: 0.0010  Loss_G: 11.1038         D(x): 0.9994
D(G(z)): 0.0004/0.0003
[1/1][1050/1583]        Loss_D: 0.0001  Loss_G: 12.1888         D(x): 0.9999
D(G(z)): 0.0000/0.0001
[1/1][1100/1583]        Loss_D: 0.0003  Loss_G: 12.5416         D(x): 1.0000
D(G(z)): 0.0002/0.0003
[1/1][1150/1583]        Loss_D: 0.0317  Loss_G: 13.4492         D(x): 0.9923
```

```
D(G(z)): 0.0004/0.0000
[1/1][1200/1583]        Loss_D: 0.0026  Loss_G: 13.1606         D(x): 0.9983
D(G(z)): 0.0007/0.0002
[1/1][1250/1583]        Loss_D: 0.0002  Loss_G: 13.5758         D(x): 0.9999
D(G(z)): 0.0002/0.0002
[1/1][1300/1583]        Loss_D: 0.0006  Loss_G: 11.7854         D(x): 0.9997
D(G(z)): 0.0004/0.0005
[1/1][1350/1583]        Loss_D: 0.0003  Loss_G: 10.9696         D(x): 0.9998
D(G(z)): 0.0002/0.0002
[1/1][1400/1583]        Loss_D: 0.0005  Loss_G: 10.9147         D(x): 0.9997
D(G(z)): 0.0003/0.0001
[1/1][1450/1583]        Loss_D: 0.0004  Loss_G: 10.9153         D(x): 1.0000
D(G(z)): 0.0004/0.0007
[1/1][1500/1583]        Loss_D: 0.0003  Loss_G: 11.0962         D(x): 1.0000
D(G(z)): 0.0002/0.0001
[1/1][1550/1583]        Loss_D: 0.0001  Loss_G: 11.4345         D(x): 1.0000
D(G(z)): 0.0000/0.0003
```

2.7 Visualise the loss

[ ]:
```python
plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses,label="G")
plt.plot(D_losses,label="D")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



2.8 Animate the generators progression

[ ]:
```
from IPython.display import HTML

fig = plt.figure(figsize=(8,8))
plt.axis("off")
ims = [[plt.imshow(np.transpose(i,(1,2,0)), animated=True)] for i in img_list]
ani = animate.ArtistAnimation(fig, ims, interval=1000, repeat_delay=1000,␣
 ↪blit=True)

HTML(ani.to_jshtml())
```

[ ]: <IPython.core.display.HTML object>