Assignment 4 Generative Adversarial Nets (Unconditional, 10 pts)

In this exercise, we will implement a Generative Adversarial Net (GAN), specifically, a Wasserstein GAN and train it on the MNIST dataset. *We recommend completing this assignment using Google Colab with Chrome Browser*.

Submit

1. (Doc A) Include the two figures at the end in the pdf generated by the latex file with Exercise 2
2. (Doc B) The completed *.ipynb file with all the command outputs (can be created by saving the file after finishing the experiment and downloading it from Colab)

Setup

1. In Colab, open tab Runtime > Change runtime type, choose *python3* and *T4 GPU*.
2. Run the following command to set up the environment. (Takes ~ 1.5 min)

```
! pip install --quiet "ipython[notebook]==7.34.0, <8.17.0" "setuptools>=68.0.0, <68.3.0" "torch==1.13.0" "matplotlib" "torchvision"
```

Let's start with importing our standard set of libraries.

```
import time
import torch
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import torchvision.utils as vutils
from torch import nn, optim, autograd
from torch.utils.data import DataLoader
from dataclasses import dataclass

%matplotlib inline
torch.set_num_threads(1)
torch.manual_seed(1)
```

```
device = torch.device("cuda:0") if torch.cuda.is_available() else torch.device("cpu")

if device == torch.device("cuda:0"):
  print('Everything looks good; continue')
else:
  # It is OK if you cannot connect to a GPU. In this case, training the model for
  # 2 epoch is sufficient to get full mark. (NOTE THAT 2 epoch takes approximately 1.5 hours to train for CPU)
  print('GPU is not detected. Make sure you have chosen the right runtime type')
```

```
Everything looks good; continue
```

Dataloaders and hyperparameters (0 pt)

```
@dataclass
class Hyperparameter:
    batchsize: int = 64
    num_epochs: int = 5
    latent_size: int = 32
    n_critic: int = 5
    critic_size: int = 1024
    generator_size: int = 1024
    critic_hidden_size: int = 1024
    gp_lambda: float = 10.
```

```
hp = Hyperparameter()

transform = transforms.Compose(
    [transforms.ToTensor(), transforms.Normalize((0.5,), (0.5,))])

dataset = torchvision.datasets.MNIST(
    "mnist", download=True, transform=transform)
dataloader = DataLoader(dataset, batch_size=hp.batchsize,
                        num_workers=1, shuffle=True, drop_last=True, pin_memory=True)
```

Building Models (2 pts)

After examining the preprocessing steps, we can now start building the models, including the generator for generating new images from random noise, and a critic of the realness of the image.

In this assignment we adopt the implementation of DCGAN, which is a direct extension of GAN, with convolutional and convolutional-transpose layers in the critic and genrator, respectively. Specifically, we will use the ConvTranspose2d layers to upscale the noise.

Moreover, we apply an improved version of Wasserstein-GAN with a Gradient Penalty (you may read Algorithm 1 to fully understand the code we are implementing).

```
# Define the generator
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()

        # Add latent embedding layer to adjust the dimension of the input (1 pt)
        self.latent_embedding = nn.Linear(hp.latent_size, hp.generator_size)

        # Transposed CNN layers to transfer noise to image
        self.tcnn = nn.Sequential(
            # input is Z, going into a convolution
            nn.ConvTranspose2d(hp.generator_size, hp.generator_size, 4, 1, 0),
            nn.BatchNorm2d(hp.generator_size),
            nn.ReLU(inplace=True),
            # upscaling
            nn.ConvTranspose2d(hp.generator_size,
                               hp.generator_size // 2, 3, 2, 1),
            nn.BatchNorm2d(hp.generator_size // 2),
            nn.ReLU(inplace=True),
            # upscaling
            nn.ConvTranspose2d(hp.generator_size // 2,
                               hp.generator_size // 4, 4, 2, 1),
            nn.BatchNorm2d(hp.generator_size // 4),
            nn.ReLU(inplace=True),
            nn.ConvTranspose2d(hp.generator_size // 4, 1, 4, 2, 1),
            nn.Tanh()
        )

    def forward(self, latent):
        vec_latent = self.latent_embedding(latent).reshape(-1, hp.generator_size, 1, 1)
        return self.tcnn(vec_latent)


# Define the critic
class Critic(nn.Module):
    def __init__(self):
        super(Critic, self).__init__()

        # CNN layers that perform downscaling
        self.cnn_net = nn.Sequential(
            nn.Conv2d(1, hp.critic_size // 4, 3, 2),
            nn.InstanceNorm2d(hp.critic_size // 4, affine=True),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(hp.critic_size // 4, hp.critic_size // 2, 3, 2),
            nn.InstanceNorm2d(hp.critic_size // 2, affine=True),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(hp.critic_size // 2, hp.critic_size, 3, 2),
            nn.InstanceNorm2d(hp.critic_size, affine=True),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Flatten(),
        )

        # Linear layers that produce the output from the features
        self.critic_net = nn.Sequential(
            nn.Linear(hp.critic_size * 4, hp.critic_hidden_size),
            nn.LeakyReLU(0.2, inplace=True),

            # Add the last layer to reflect the output (1 pt)
            nn.Linear(hp.critic_hidden_size, 1)
        )

    def forward(self, image):
        cnn_features = self.cnn_net(image)
        return self.critic_net(cnn_features)
```

Before Training

Next we define the two models and the optimizers. We use the [AdamW](https://pytorch.org/docs/stable/generated/torch.optim.AdamW.html) algorithm.

```
critic, generator = Critic().to(device), Generator().to(device)

critic_optimizer = optim.AdamW(critic.parameters(), lr=1e-4,betas=(0., 0.9))
generator_optimizer = optim.AdamW(generator.parameters(), lr=1e-4,betas=(0., 0.9))
```

Training pipeline (6 points)

Finally, we perform training on the two networks. The training consists of two steps: (1) Updating discriminators for n_critic steps (such that we have an optimal critic): here we use an aggregation of three loss functions, (a) The real loss (the output scalar of the critic for real images); (b) The fake loss (same value for fake images); (c) The gradient penalty. (2) Updating generators by only considering the fake loss (to fool the critic).

```
img_list, generator_losses, critic_losses = [], [], []
iters = 0
fixed_noise = torch.randn((64, hp.latent_size), device=device)
grad_tensor = torch.ones((hp.batchsize, 1), device=device)
start_time = time.time()
for epoch in range(hp.num_epochs):
    for batch_idx, data in enumerate(dataloader, 0):
        real_images = data[0].to(device)

        # Update Critic
        critic_optimizer.zero_grad()

        # (a) Real loss
```

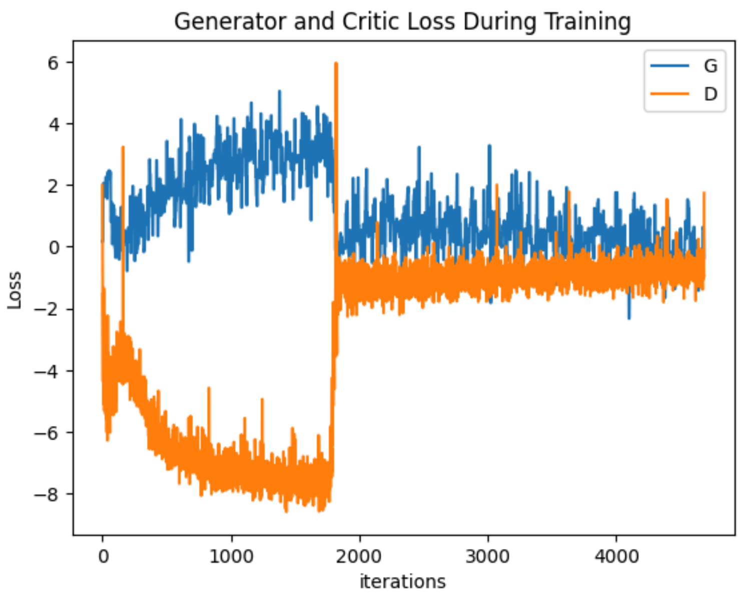
```
        # (a) Real loss
        critic_output_real = critic(real_images)
        critic_loss_real = critic_output_real.mean()

        # (b) Fake loss
        # (1) Generating a noise tensor (of dimension (batch_size, latent_size)), you are required to
        # use the hyperparameters in the hp class (0.5 pt)
        noise = torch.randn((hp.batchsize, hp.latent_size), device=device)

        # (2) Generate fake images using the generator (hint: you are not supposed to perform gradient
        # update on the generator) (1.5 pts)
        with torch.no_grad():
            fake_image = generator(noise)

        # (3) Calculate the fake loss using the output of the generator (1 pt)
        critic_output_fake = critic(fake_image)
        critic_loss_fake = critic_output_fake.mean()

        #  (c) Gradient penalty
        alpha = torch.rand((hp.batchsize, 1, 1, 1), device=device)
        interpolates = (alpha * real_images + ((1. - alpha)
                        * fake_image)).requires_grad_(True)
        d_interpolates = critic(interpolates)
        gradients = autograd.grad(
            d_interpolates, interpolates, grad_tensor, create_graph=True, only_inputs=True)[0]
        gradient_penalty = hp.gp_lambda * (
            (gradients.view(hp.batchsize, -1).norm(dim=1) - 1.) ** 2).mean()

        # Implement the aggregated loss using the above three components, be careful with the signs (1 pt)
        critic_loss = critic_loss_fake - critic_loss_real + gradient_penalty

        critic_loss.backward()
        critic_optimizer.step()

        if batch_idx % hp.n_critic == 0:
            # Update Generator
            generator_optimizer.zero_grad()

            # Implement the generator loss (2 pts)
            noise = torch.randn((hp.batchsize, hp.latent_size), device=device)
            fake_image = generator(noise)
            critic_output_fake = critic(fake_image)
            generator_loss = -critic_output_fake.mean()

            generator_loss.backward()
            generator_optimizer.step()

        # Output training stats
        if batch_idx % 100 == 0:
            elapsed_time = time.time() - start_time
            print(f"[{epoch:>2}/{hp.num_epochs}][{iters:>7}][{elapsed_time:8.2f}s]\t"
                  f"d_loss/g_loss: {critic_loss.item():4.2}/{generator_loss.item():4.2}\t")

        # Save Losses for plotting later
        generator_losses.append(generator_loss.item())
        critic_losses.append(critic_loss.item())

        # Check how the generator is doing by saving G's output on fixed_noise
        if (iters % 500 == 0) or ((epoch == hp.num_epochs - 1) and (batch_idx == len(dataloader) - 1)):
            with torch.no_grad():
                fake_images = generator(fixed_noise).cpu()
            img_list.append(vutils.make_grid(
                fake_images, padding=2, normalize=True))

        iters += 1
```

```
[ 0/5][      0][    0.25s]	d_loss/g_loss:  2.0/0.17
[ 0/5][    100][   17.78s]	d_loss/g_loss: -5.1/-0.35
[ 0/5][    200][   35.42s]	d_loss/g_loss: -4.0/0.62
[ 0/5][    300][   52.67s]	d_loss/g_loss: -4.9/ 1.2
[ 0/5][    400][   69.67s]	d_loss/g_loss: -6.4/ 1.7
[ 0/5][    500][   86.62s]	d_loss/g_loss: -7.0/ 3.4
[ 0/5][    600][  103.74s]	d_loss/g_loss: -7.2/ 1.8
[ 0/5][    700][  120.90s]	d_loss/g_loss: -6.8/ 2.0
[ 0/5][    800][  138.00s]	d_loss/g_loss: -6.7/ 2.5
[ 0/5][    900][  155.06s]	d_loss/g_loss: -7.1/ 1.5
[ 1/5][    937][  161.56s]	d_loss/g_loss: -7.3/ 2.8
[ 1/5][   1037][  178.64s]	d_loss/g_loss: -7.6/ 3.7
[ 1/5][   1137][  195.72s]	d_loss/g_loss: -7.7/ 3.0
[ 1/5][   1237][  212.80s]	d_loss/g_loss: -7.5/ 2.2
[ 1/5][   1337][  229.88s]	d_loss/g_loss: -8.0/ 2.7
[ 1/5][   1437][  247.04s]	d_loss/g_loss: -7.6/ 2.8
[ 1/5][   1537][  264.12s]	d_loss/g_loss: -7.6/ 1.9
[ 1/5][   1637][  281.21s]	d_loss/g_loss: -7.9/ 3.0
[ 1/5][   1737][  298.30s]	d_loss/g_loss: -7.7/ 2.6
[ 1/5][   1837][  315.33s]	d_loss/g_loss: -1.8/-0.14
[ 2/5][   1874][  321.83s]	d_loss/g_loss: -1.4/0.041
[ 2/5][   1974][  338.93s]	d_loss/g_loss: -1.8/ 1.1
[ 2/5][   2074][  356.08s]	d_loss/g_loss: -1.5/0.78
[ 2/5][   2174][  373.14s]	d_loss/g_loss: -1.5/0.12
[ 2/5][   2274][  390.19s]	d_loss/g_loss: -1.3/-0.24
[ 2/5][   2374][  407.26s]	d_loss/g_loss: -1.4/ 1.7
[ 2/5][   2474][  424.34s]	d_loss/g_loss: -0.98/ 0.6
[ 2/5][   2574][  441.49s]	d_loss/g_loss: -1.1/0.26
[ 2/5][   2674][  458.55s]	d_loss/g_loss: -1.5/0.65
[ 2/5][   2774][  475.59s]	d_loss/g_loss: -1.0/0.59
[ 3/5][   2811][  482.10s]	d_loss/g_loss: -0.042/-0.2
[ 3/5][   2911][  499.19s]	d_loss/g_loss: -1.1/0.62
[ 3/5][   3011][  516.31s]	d_loss/g_loss: -1.6/ 3.3
[ 3/5][   3111][  533.37s]	d_loss/g_loss: -1.2/0.41
[ 3/5][   3211][  550.49s]	d_loss/g_loss: -1.1/-0.27
[ 3/5][   3311][  567.63s]	d_loss/g_loss: -1.6/ 1.0
[ 3/5][   3411][  584.67s]	d_loss/g_loss: -1.4/0.57
[ 3/5][   3511][  601.81s]	d_loss/g_loss: -0.95/-0.13
```

```
[ 3/5][   3611][  618.87s]      d_loss/g_loss: -0.98/ 1.9
[ 3/5][   3711][  635.95s]      d_loss/g_loss: -1.4/0.93
[ 4/5][   3748][  642.43s]      d_loss/g_loss: -0.32/-0.75
[ 4/5][   3848][  659.49s]      d_loss/g_loss: -1.3/ 1.0
[ 4/5][   3948][  676.60s]      d_loss/g_loss: -0.99/-1.1
[ 4/5][   4048][  693.70s]      d_loss/g_loss: -1.1/0.24
[ 4/5][   4148][  710.76s]      d_loss/g_loss: -0.88/-0.73
[ 4/5][   4248][  727.85s]      d_loss/g_loss: -1.3/0.055
[ 4/5][   4348][  744.89s]      d_loss/g_loss: -0.73/-0.93
[ 4/5][   4448][  762.02s]      d_loss/g_loss: -0.85/0.0035
[ 4/5][   4548][  779.11s]      d_loss/g_loss: -1.1/0.76
[ 4/5][   4648][  796.18s]      d_loss/g_loss: -0.96/-0.41
```

Visualization (2 pts)

```
# Visualize the loss
# include the figure in the latex file (1 pt)
plt.title("Generator and Critic Loss During Training")
plt.plot(generator_losses, label="G")
plt.plot(critic_losses, label="D")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()
```




```
# Visualize the generation (you may scroll to see the animation of training)
# include the final figure in the latex file (1 pt)
import matplotlib.animation as animation
from IPython.display import HTML
# %%capture
fig = plt.figure(figsize=(8, 8))
plt.axis("off")
ims = [[plt.imshow(i.permute(1, 2, 0), animated=True)] for i in img_list]
ani = animation.ArtistAnimation(
    fig, ims, interval=1000, repeat_delay=1000, blit=True)

HTML(ani.to_jshtml())
```