Assignment 3

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Problem 1

(a). CNNs are made for handling images, which are good at recognizing different parts of an image and understanding how these parts relate to each other, which is crucial for figuring out what's in the image.

CNNs deal with images more efficiently, required less computing power, making them faster and better suited for dealing with lots of images.

(b). RNNs are better for tasks where the order or sequence of things matters, like predicting the next word in a sentence. But this isn't usually important for just looking at a single image.

RNNs can remember information from previous inputs, which is helpful for tasks where history or context is important.

Problem 2

Since $h_t = x_t - h_{t-1}$, assume $h_0 = 0$
So $h_1 = x_1 - h_0 = x_1,\ h_2 = x_2 - h_1 = x_2 - x_1,\ h_3 = x_3 - h_2 = x_1 - x_2 + x_3$
Assuming final step $t = 2n$, $h_{2n} = -\sum_{i=1}^{n} x_{2i-1} + \sum_{i=1}^{n} x_{2i}$, $y_{2n} = sigmoid(500h_{2n})$
Therefore, y_{2n} will be the sigmoid function applied to 500 times the difference between the sum of all even-positioned inputs and the sum of all odd-positioned inputs in the sequence.

Problem 3

1. Sparse Attention Patterns: instead of each token attending to every other token in the sequence, sparse attention patterns restrict attention to a subset of preceding tokens.
   Pros: This directly reduces the complexity to O(T) if the window size k is constant and independent of T.
   Cons: This could potentially ignore long-range dependencies that are outside the fixed window.
2. Low-Rank Approximations: self-attention matrix can be approximated by low-rank matrices.
   Pros: Low-rank approximations can significantly reduce the number of computations, the complexity to O(T).
   Cons: The main drawback is the loss of information due to approximation, which could lead to worse performance if the approximation does not capture enough of the relevant information.

Problem 4

```
import torch
from torchvision import datasets
import torch.nn as nn
from torch.utils.data import DataLoader
from torchvision import transforms
import numpy as np
import os
from matplotlib.pyplot import imsave
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
```

```
# A transform to convert the images to tensor and normalize their RGB values
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize(mean=[0.5], std=[0.5])]
)

data = datasets.MNIST(root='../data/', train=True, transform=transform, download=True)
# data = datasets.FashionMNIST(root='../data/', train=True, transform=transform,
download=True)

batch_size = 64
data_loader = DataLoader(dataset=data, batch_size=batch_size, shuffle=True, drop_last=True)
```

```
def to_onehot(x, num_classes=10):
    assert isinstance(x, int) or isinstance(x, (torch.LongTensor, torch.cuda.LongTensor))
    if isinstance(x, int):
        c = torch.zeros(1, num_classes).long()
        c[0][x] = 1
    else:
        x = x.cpu()
        c = torch.LongTensor(x.size(0), num_classes)
        c.zero_()
        c.scatter_(1, x, 1) # dim, index, src value
    return c
```

```
def get_sample_image(G, DEVICE, n_noise=100):
    img = np.zeros([280, 280])
    for j in range(10):
        c = torch.zeros([10, 10]).to(DEVICE)
        c[:, j] = 1
        z = torch.randn(10, n_noise).to(DEVICE)
        y_hat = G(z,c).view(10, 28, 28)
        result = y_hat.cpu().data.numpy()
        img[j*28:(j+1)*28] = np.concatenate([x for x in result], axis=-1)
    return img
```

```
def get_sample_image(G, DEVICE, n_noise=100):
    img = np.zeros([280, 280])
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        z = torch.randn(10, n_noise).to(DEVICE)
        y_hat = G(z).view(10, 28, 28)
        result = y_hat.cpu().data.numpy()
        img[j*28:(j+1)*28] = np.concatenate([x for x in result], axis=-1)
    return img
```

```
class Generator(nn.Module):
    def __init__(self, input_size=100, num_classes=10, image_size=28*28):
        super(Generator, self).__init__()
        self.network = nn.Sequential(
            nn.Linear(input_size+num_classes, 128), # auxillary dimension for label
            nn.LeakyReLU(0.2),
            nn.Linear(128, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 512),
            nn.BatchNorm1d(512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 1024),
            nn.BatchNorm1d(1024),
            nn.LeakyReLU(0.2),
            nn.Linear(1024, image_size),
            nn.Tanh()
        )

    def forward(self, x, c):
        x, c = x.view(x.size(0), -1), c.view(c.size(0), -1).float()
        v = torch.cat((x, c), 1) # v: [input, label] concatenated vector
        y_ = self.network(v)
        y_ = y_.view(x.size(0), 1, 28, 28)
        return y_

class Discriminator(nn.Module):
    def __init__(self, input_size=28*28, num_classes=10, num_output=1):
        super(Discriminator, self).__init__()
        self.network = nn.Sequential(
            nn.Linear(input_size+num_classes, 512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, num_output),
            nn.Sigmoid(),
        )
```

```
    def forward(self, x, c):
        x, c = x.view(x.size(0), -1), c.view(c.size(0), -1).float()
        v = torch.cat((x, c), 1) # v: [input, label] concatenated vector
        y_ = self.network(v)
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```

```
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    def __init__(self, input_size=100, image_size=28*28):
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        self.network = nn.Sequential(
            nn.Linear(input_size, 128),
            nn.LeakyReLU(0.2),
            nn.Linear(128, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 512),
            nn.BatchNorm1d(512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 1024),
            nn.BatchNorm1d(1024),
            nn.LeakyReLU(0.2),
            nn.Linear(1024, image_size),
            nn.Tanh()
        )

    def forward(self, x):
        x = x.view(x.size(0), -1)
        y_ = self.network(x)
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        return y_

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            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, num_output),
            nn.Sigmoid(),
        )

    def forward(self, x):
        x = x.view(x.size(0), -1)
        y_ = self.network(x)
        return y_
```

```
MODEL_NAME = 'ConditionalGAN'
DEVICE = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

D = Discriminator().to(DEVICE) # randomly intialized
G = Generator().to(DEVICE) # randomly initialized

max_epoch = 10
step = 0
n_noise = 100 # size of noise vector

criterion = nn.BCELoss()
D_opt = torch.optim.Adam(D.parameters(), lr=0.0002, betas=(0.5, 0.999))
G_opt = torch.optim.Adam(G.parameters(), lr=0.0002, betas=(0.5, 0.999))

# We will denote real images as 1s and fake images as 0s
# This is why we needed to drop the last batch of the data loader
all_ones = torch.ones([batch_size, 1]).to(DEVICE) # Discriminator label: real
all_zeros = torch.zeros([batch_size, 1]).to(DEVICE) # Discriminator Label: fake
```

```
MODEL_NAME = 'GAN'
DEVICE = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


D = Discriminator().to(DEVICE) # randomly initialized
G = Generator().to(DEVICE) # randomly initialized

max_epoch = 10
step = 0
n_noise = 100  # size of the noise vector

criterion = nn.BCELoss()
D_opt = torch.optim.Adam(D.parameters(), lr=0.0002, betas=(0.5, 0.999))
G_opt = torch.optim.Adam(G.parameters(), lr=0.0002, betas=(0.5, 0.999))

all_ones = torch.ones([batch_size, 1]).to(DEVICE)  # Discriminator label: real
all_zeros = torch.zeros([batch_size, 1]).to(DEVICE)  # Discriminator label: fake
```

```
# a directory to save the generated images
if not os.path.exists('samples'):
    os.makedirs('samples')

for epoch in range(max_epoch):
    for idx, (images, class_labels) in enumerate(data_loader):
        # Training Discriminator
        x = images.to(DEVICE)
```

```
        class_labels = class_labels.view(batch_size, 1) # add singleton dimension so
batch_size x 1
        class_labels = to_onehot(class_labels).to(DEVICE)
        x_outputs = D(x, class_labels) # input includes labels
        D_x_loss = criterion(x_outputs, all_ones) # Discriminator loss for real images

        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z, class_labels), class_labels) # input to both generator and
discriminator includes labels
        D_z_loss = criterion(z_outputs, all_zeros) # Discriminator loss for fake images
        D_loss = D_x_loss + D_z_loss # Total Discriminator loss

        D.zero_grad()
        D_loss.backward()
        D_opt.step()

        # Training Generator
        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z, class_labels), class_labels)
        G_loss = -1 * criterion(z_outputs, all_zeros) # Generator loss is negative
disciminator loss

        G.zero_grad()
        G_loss.backward()
        G_opt.step()

        if step % 500 == 0:
            print('Epoch: {}/{}, Step: {}, D Loss: {}, G Loss: {}'.format(epoch, max_epoch,
step, D_loss.item(), G_loss.item()))

        if step % 1000 == 0:
            G.eval()
            img = get_sample_image(G, DEVICE, n_noise)
            imsave('samples/{}_step{}.jpg'.format(MODEL_NAME, str(step).zfill(3)), img,
cmap='gray')
            G.train()
        step += 1
```

```
Epoch: 0/10, Step: 0, D Loss: 1.3514288663864136, G Loss: -0.6830189824104309
Epoch: 0/10, Step: 500, D Loss: 1.1450117826461792, G Loss: -0.5035810470581055
Epoch: 1/10, Step: 1000, D Loss: 1.1381268501281738, G Loss: -0.4759160578250885
Epoch: 1/10, Step: 1500, D Loss: 1.2079648971557617, G Loss: -0.6697063446044922
Epoch: 2/10, Step: 2000, D Loss: 1.2449171543121338, G Loss: -0.43948161602020264
Epoch: 2/10, Step: 2500, D Loss: 1.2173736095428467, G Loss: -0.5826414823532104
Epoch: 3/10, Step: 3000, D Loss: 1.3378918170928955, G Loss: -0.5487537384033203
Epoch: 3/10, Step: 3500, D Loss: 1.3011475801467896, G Loss: -0.6142688393592834
Epoch: 4/10, Step: 4000, D Loss: 1.2872161865234375, G Loss: -0.6764382123947144
Epoch: 4/10, Step: 4500, D Loss: 1.3877155780792236, G Loss: -0.739016592502594
```

```
Epoch: 5/10, Step: 5000, D Loss: 1.3732285499572754, G Loss: -0.9222396016120911
Epoch: 5/10, Step: 5500, D Loss: 1.2177181243896484, G Loss: -0.5097173452377319
Epoch: 6/10, Step: 6000, D Loss: 1.3754500150680542, G Loss: -0.48548728227615356
Epoch: 6/10, Step: 6500, D Loss: 1.2071152925491333, G Loss: -0.5240878462791443
Epoch: 7/10, Step: 7000, D Loss: 1.298447847366333, G Loss: -0.6028752326965332
Epoch: 8/10, Step: 7500, D Loss: 1.2622554302215576, G Loss: -0.5587561726570129
Epoch: 8/10, Step: 8000, D Loss: 1.35408616065979, G Loss: -0.553693413734436
Epoch: 9/10, Step: 8500, D Loss: 1.3651952743530273, G Loss: -0.5998132228851318
Epoch: 9/10, Step: 9000, D Loss: 1.303840160369873, G Loss: -0.62741619348526
```

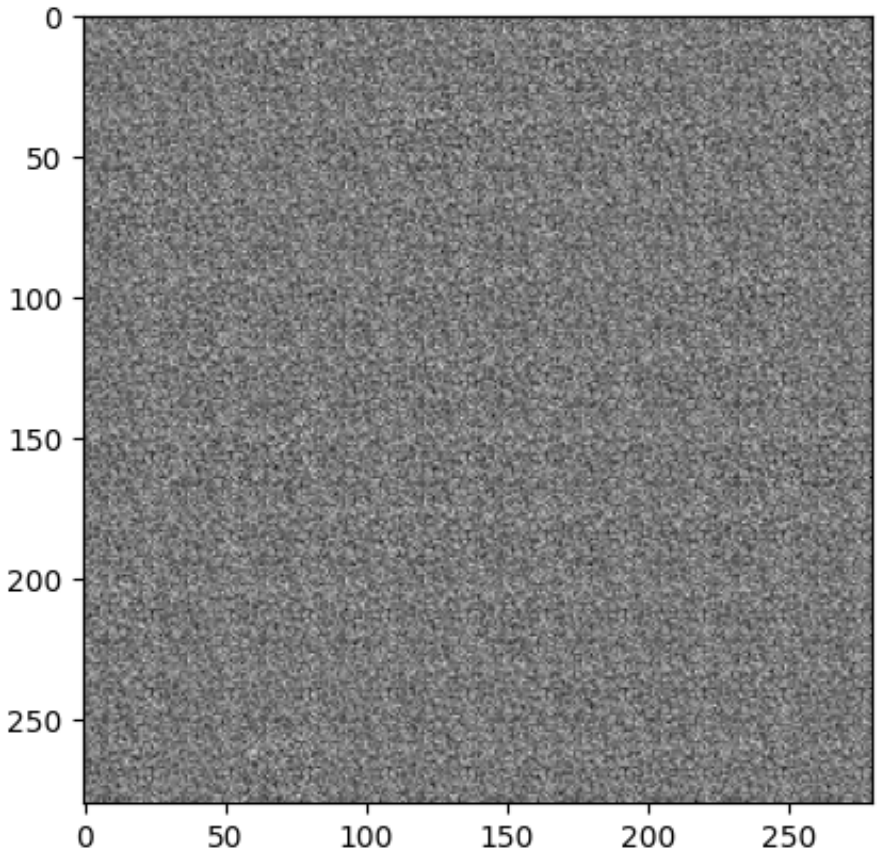
```
# a directory to save the generated images
if not os.path.exists('samples'):
    os.makedirs('samples')

for epoch in range(max_epoch):
    for idx, (images, _) in enumerate(data_loader):  # No class labels
        # Training Discriminator
        x = images.to(DEVICE)
        x_outputs = D(x)  # No class labels
        D_x_loss = criterion(x_outputs, all_ones)  # Discriminator loss for real images

        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z))  # No class labels
        D_z_loss = criterion(z_outputs, all_zeros)  # Discriminator loss for fake images
        D_loss = D_x_loss + D_z_loss  # Total Discriminator loss

        D.zero_grad()
        D_loss.backward()
        D_opt.step()

        # Training Generator
        z = torch.randn(batch_size, n_noise).to(DEVICE)
        z_outputs = D(G(z))
        G_loss = criterion(z_outputs, all_ones)  # Generator loss is negative disciminator
loss

        G.zero_grad()
        G_loss.backward()
        G_opt.step()

        if step % 500 == 0:
            print('Epoch: {}/{}, Step: {}, D Loss: {}, G Loss: {}'.format(epoch, max_epoch,
step, D_loss.item(), G_loss.item()))

        if step % 1000 == 0:
            G.eval()
            img = get_sample_image(G, DEVICE, n_noise)
```

```
            imsave('samples/{}_step{}.jpg'.format(MODEL_NAME, str(step).zfill(3)), img,
cmap='gray')
            G.train()
        step += 1
```

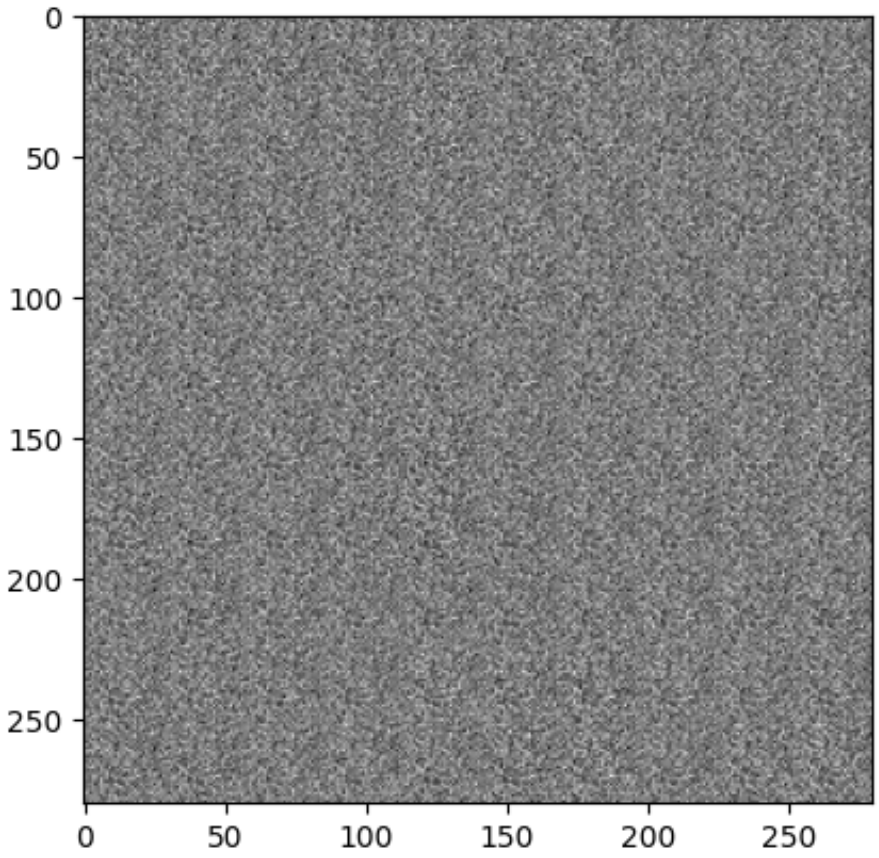
```
Epoch: 0/10, Step: 0, D Loss: 1.362381935119629, G Loss: 0.7160969972610474
Epoch: 0/10, Step: 500, D Loss: 1.2294949293136597, G Loss: 1.4084221124649048
Epoch: 1/10, Step: 1000, D Loss: 1.3241937160491943, G Loss: 1.1526758670806885
Epoch: 1/10, Step: 1500, D Loss: 1.4414507150650024, G Loss: 0.6690715551376343
Epoch: 2/10, Step: 2000, D Loss: 1.354343295097351, G Loss: 0.7686076164245605
Epoch: 2/10, Step: 2500, D Loss: 1.2374329566955566, G Loss: 0.9881440997123718
Epoch: 3/10, Step: 3000, D Loss: 1.3842191696166992, G Loss: 1.3369228839874268
Epoch: 3/10, Step: 3500, D Loss: 1.2120521068572998, G Loss: 0.9725512862205505
Epoch: 4/10, Step: 4000, D Loss: 1.338620662689209, G Loss: 1.0967302322387695
Epoch: 4/10, Step: 4500, D Loss: 1.3118302822113037, G Loss: 0.9211345314979553
Epoch: 5/10, Step: 5000, D Loss: 1.3415734767913818, G Loss: 0.9145141243934631
Epoch: 5/10, Step: 5500, D Loss: 1.3334400653839111, G Loss: 0.7846530079841614
Epoch: 6/10, Step: 6000, D Loss: 1.2255659103393555, G Loss: 0.8414651155471802
Epoch: 6/10, Step: 6500, D Loss: 1.3331624269485474, G Loss: 0.8945848345756531
Epoch: 7/10, Step: 7000, D Loss: 1.2973811626434326, G Loss: 1.0530595779418945
Epoch: 8/10, Step: 7500, D Loss: 1.2927491664886475, G Loss: 0.7726222276687622
Epoch: 8/10, Step: 8000, D Loss: 1.2967383861541748, G Loss: 0.8315809965133667
Epoch: 9/10, Step: 8500, D Loss: 1.324432134628296, G Loss: 0.7745360732078552
Epoch: 9/10, Step: 9000, D Loss: 1.327396273612976, G Loss: 0.7497842311859131
```

Now let's plot these images.

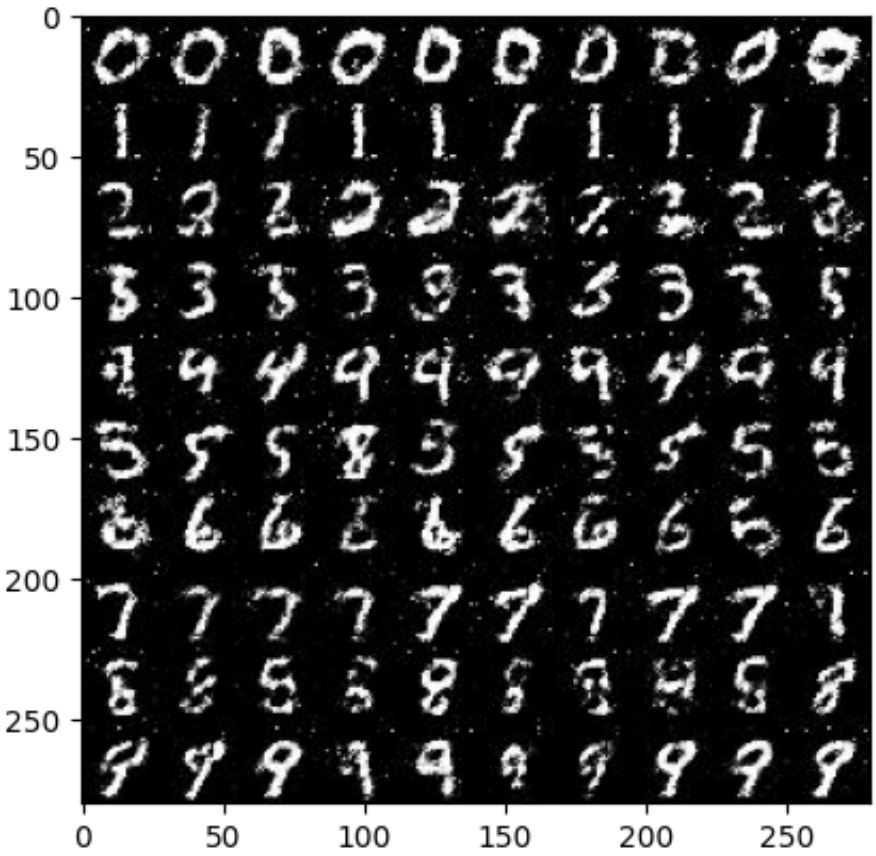
```
img = mpimg.imread('samples/ConditionalGAN_step000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



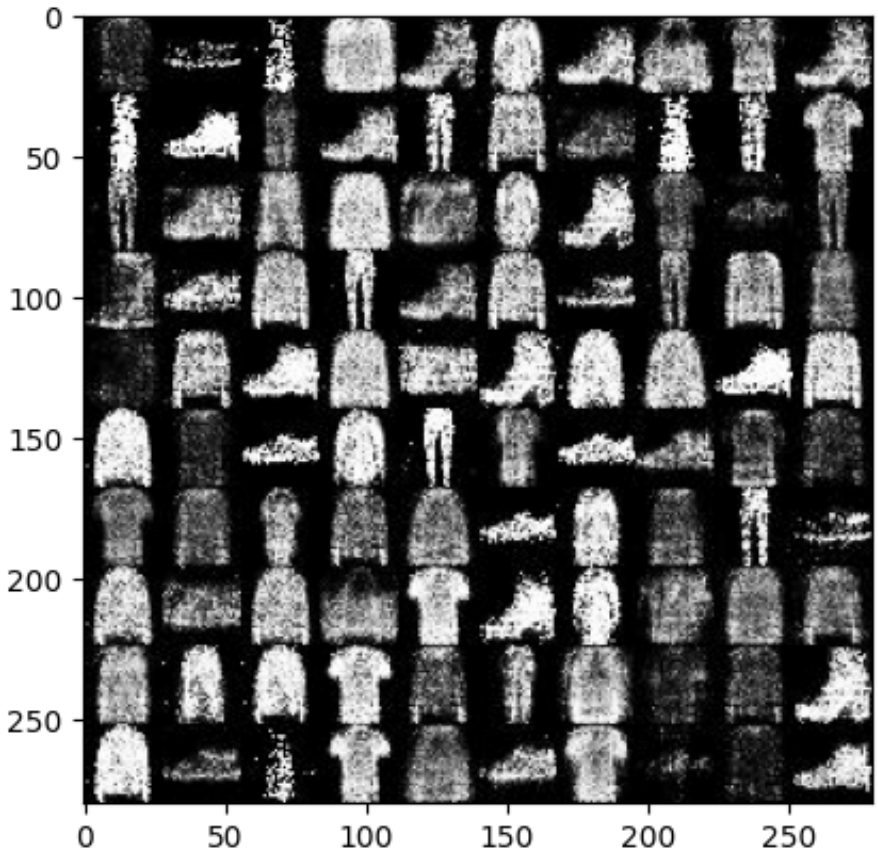

```
img = mpimg.imread('/content/samples/GAN_step000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



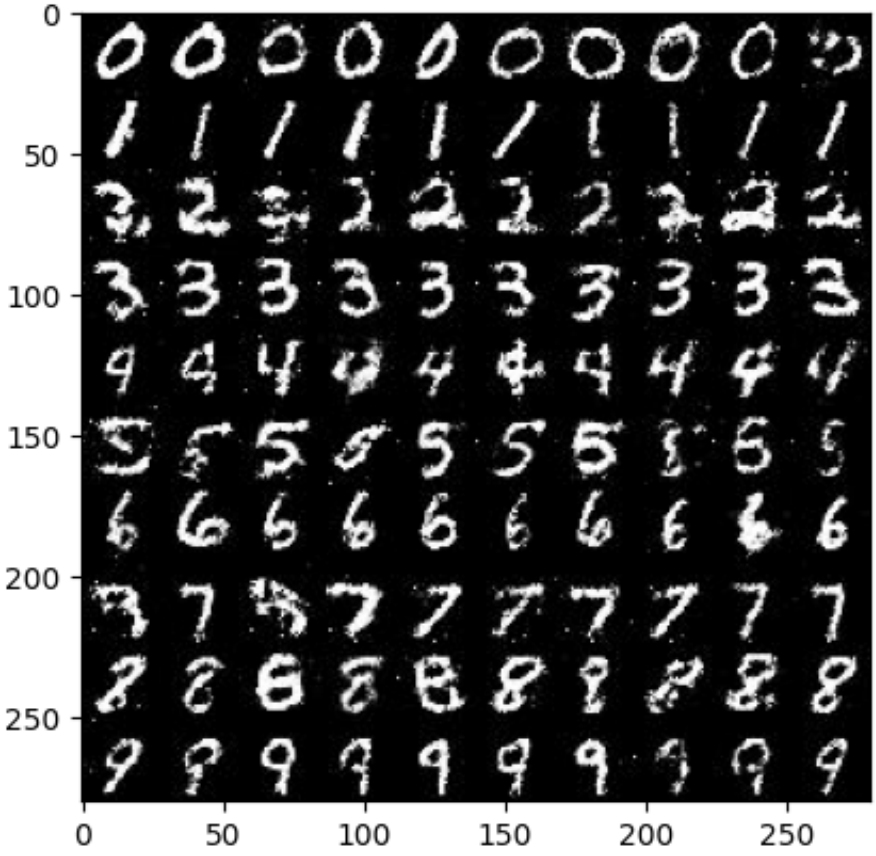

```
img = mpimg.imread('samples/ConditionalGAN_step5000.jpg')
imgplot = plt.imshow(img)
plt.show()
```



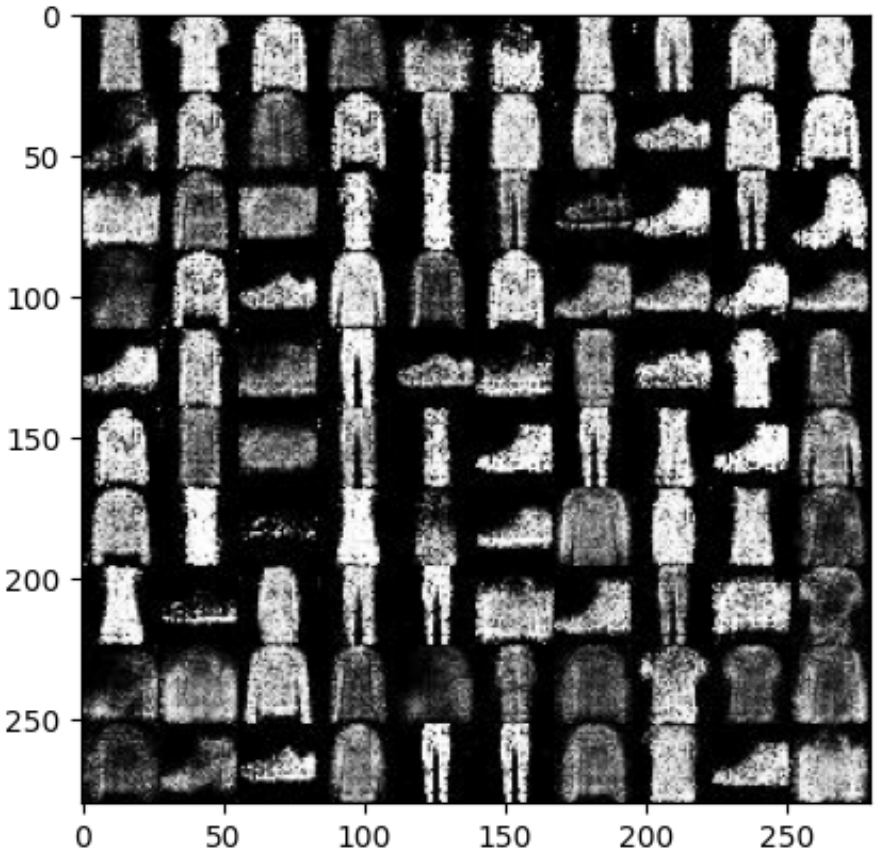

```
img = mpimg.imread('/content/samples/GAN_step5000.jpg')
imgplot = plt.imshow(img)
plt.show()
```




```
img = mpimg.imread('samples/ConditionalGAN_step9000.jpg')
imgplot = plt.imshow(img)
plt.show()
```




```
img = mpimg.imread('/content/samples/GAN_step9000.jpg')
imgplot = plt.imshow(img)
plt.show()
```




```
import torchvision.utils as vutils

def plot_grid_of_images(images, nrow=10, normalize=True):
    grid = vutils.make_grid(images, nrow=nrow, normalize=normalize, padding=2,
scale_each=True)

    np_grid = grid.numpy().transpose((1, 2, 0))

    plt.figure(figsize=(5, 5))
    plt.imshow(np_grid)
    plt.axis('off')
    plt.show()

num_images = 100
images = []
for img, _ in data_loader:
    images.append(img)
    if len(images) * img.size(0) >= num_images:
        break
images = torch.cat(images, dim=0)[:num_images]
plot_grid_of_images(images)
```

It is clear that GAN preform well in generating FashionMNIST image. Compare to Conditional GAN, the images generated by GAN have more clear edge and better shape. Some of the number generated by CGAN could not be recognized well.