

dlnd_face_generation

February 10, 2019

1 Face Generation

In this project, you'll define and train a DCGAN on a dataset of faces. Your goal is to get a generator network to generate *new* images of faces that look as realistic as possible!

The project will be broken down into a series of tasks from **loading in data to defining and training adversarial networks**. At the end of the notebook, you'll be able to visualize the results of your trained Generator to see how it performs; your generated samples should look like fairly realistic faces with small amounts of noise.

1.0.1 Get the Data

You'll be using the [CelebFaces Attributes Dataset \(CelebA\)](#) to train your adversarial networks.

This dataset is more complex than the number datasets (like MNIST or SVHN) you've been working with, and so, you should prepare to define deeper networks and train them for a longer time to get good results. It is suggested that you utilize a GPU for training.

1.0.2 Pre-processed Data

Since the project's main focus is on building the GANs, we've done *some* of the pre-processing for you. Each of the CelebA images has been cropped to remove parts of the image that don't include a face, then resized down to 64x64x3 NumPy images. Some sample data is show below.

If you are working locally, you can download this data [by clicking here](#)

This is a zip file that you'll need to extract in the home directory of this notebook for further loading and processing. After extracting the data, you should be left with a directory of data processed_celeba_small/

```
In [1]: # can comment out after executing
        !unzip processed_celeba_small.zip
```

```
unzip: cannot find or open processed_celeba_small.zip, processed_celeba_small.zip.zip or proc
```

```
In [1]: data_dir = 'processed_celeba_small/'
```

```
"""
DON'T MODIFY ANYTHING IN THIS CELL
```

```

"""
import pickle as pkl
import matplotlib.pyplot as plt
import numpy as np
import problem_unittests as tests
#import helper

%matplotlib inline

```

1.1 Visualize the CelebA Data

The [CelebA](#) dataset contains over 200,000 celebrity images with annotations. Since you're going to be generating faces, you won't need the annotations, you'll only need the images. Note that these are color images with 3 color channels (RGB) each.

1.1.1 Pre-process and Load the Data

Since the project's main focus is on building the GANs, we've done *some* of the pre-processing for you. Each of the CelebA images has been cropped to remove parts of the image that don't include a face, then resized down to 64x64x3 NumPy images. This *pre-processed* dataset is a smaller subset of the very large CelebA data.

There are a few other steps that you'll need to **transform** this data and create a **DataLoader**.

Exercise: Complete the following `get_dataloader` function, such that it satisfies these requirements:

- Your images should be square, Tensor images of size `image_size x image_size` in the x and y dimension.
- Your function should return a `DataLoader` that shuffles and batches these Tensor images.

ImageFolder To create a dataset given a directory of images, it's recommended that you use PyTorch's [ImageFolder](#) wrapper, with a root directory `processed_celeba_small/` and data transformation passed in.

```

In [2]: # necessary imports
import torch
from torchvision import datasets
from torchvision import transforms

In [3]: def get_dataloader(batch_size, image_size, data_dir='processed_celeba_small/'):
    """
    Batch the neural network data using DataLoader
    :param batch_size: The size of each batch; the number of images in a batch
    :param img_size: The square size of the image data (x, y)
    :param data_dir: Directory where image data is located
    :return: DataLoader with batched data
    """

```

```

# TODO: Implement function and return a dataloader

image_transforms = transforms.Compose([transforms.Resize(image_size),
                                       transforms.ToTensor(),
                                       ])

dataloader = torch.utils.data.DataLoader(datasets.ImageFolder(data_dir, transform=
                                                             , shuffle=True, batch_size=batch_size)

return dataloader

```

1.2 Create a DataLoader

Exercise: Create a DataLoader celeba_train_loader with appropriate hyperparameters. Call the above function and create a dataloader to view images. * You can decide on any reasonable batch_size parameter * Your image_size **must be** 32. Resizing the data to a smaller size will make for faster training, while still creating convincing images of faces!

```

In [4]: # Define function hyperparameters
batch_size = 20
img_size = 32

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

# Call your function and get a dataloader
celeba_train_loader = get_dataloader(batch_size, img_size)

```

Next, you can view some images! You should see square images of somewhat-centered faces.

Note: You'll need to convert the Tensor images into a NumPy type and transpose the dimensions to correctly display an image, suggested imshow code is below, but it may not be perfect.

```

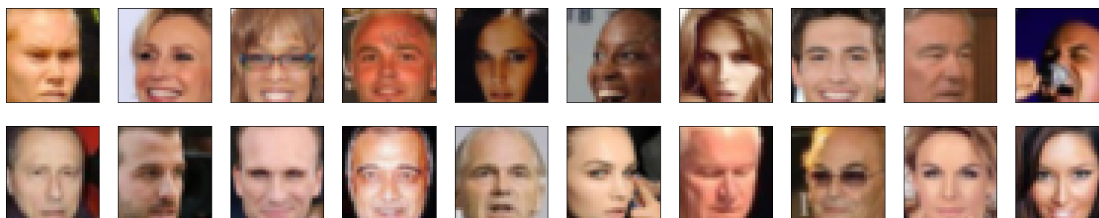
In [5]: # helper display function
def imshow(img):
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

# obtain one batch of training images
dataiter = iter(celeba_train_loader)
images, _ = dataiter.next() # _ for no labels

# plot the images in the batch, along with the corresponding labels
fig = plt.figure(figsize=(20, 4))
plot_size=20
for idx in np.arange(plot_size):
    ax = fig.add_subplot(2, plot_size/2, idx+1, xticks=[], yticks=[])
    imshow(images[idx])

```



Exercise: Pre-process your image data and scale it to a pixel range of -1 to 1 You need to do a bit of pre-processing; you know that the output of a tanh activated generator will contain pixel values in a range from -1 to 1, and so, we need to rescale our training images to a range of -1 to 1. (Right now, they are in a range from 0-1.)

```
In [6]: # TODO: Complete the scale function
def scale(x, feature_range=(-1, 1)):
    ''' Scale takes in an image x and returns that image, scaled
        with a feature_range of pixel values from -1 to 1.
        This function assumes that the input x is already scaled from 0-1. '''
    # assume x is scaled to (0, 1)
    # scale to feature_range and return scaled x

    return x*(feature_range[1] - feature_range[0]) + feature_range[0]
```

```
In [7]: """
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

# check scaled range
# should be close to -1 to 1
img = images[0]
scaled_img = scale(img)

print('Min: ', scaled_img.min())
print('Max: ', scaled_img.max())
```

```
Min:  tensor(-0.9059)
Max:  tensor(0.8431)
```

2 Define the Model

A GAN is comprised of two adversarial networks, a discriminator and a generator.

2.1 Discriminator

Your first task will be to define the discriminator. This is a convolutional classifier like you've built before, only without any maxpooling layers. To deal with this complex data, it's suggested you use a deep network with **normalization**. You are also allowed to create any helper functions that may be useful.

Exercise: Complete the Discriminator class

- The inputs to the discriminator are 32x32x3 tensor images
- The output should be a single value that will indicate whether a given image is real or fake

```
In [8]: import torch.nn as nn
        import torch.nn.functional as F
```

```
In [9]: class Discriminator(nn.Module):
```

```
    def __init__(self, conv_dim):
        """
        Initialize the Discriminator Module
        :param conv_dim: The depth of the first convolutional layer
        """
        super(Discriminator, self).__init__()

        # complete init function
        self.conv_dim = conv_dim
        self.conv1 = nn.Conv2d(3, conv_dim, kernel_size=4, stride=2, padding=1, bias=False)
        self.batch_norm1 = nn.BatchNorm2d(conv_dim)
        self.conv2 = nn.Conv2d(conv_dim, conv_dim*2, kernel_size=4, stride=2, padding=1)
        self.batch_norm2 = nn.BatchNorm2d(conv_dim*2)
        self.conv3 = nn.Conv2d(conv_dim*2, conv_dim*4, kernel_size=4, stride=2, padding=1)
        self.batch_norm3 = nn.BatchNorm2d(conv_dim*4)
        self.conv4 = nn.Conv2d(conv_dim*4, conv_dim*8, kernel_size=4, stride=2, padding=1)
        self.batch_norm4 = nn.BatchNorm2d(conv_dim*8)
        self.conv5 = nn.Conv2d(conv_dim*8, conv_dim*16, kernel_size=4, stride=2, padding=1)
        self.fc = nn.Linear(conv_dim*4*4, 1)

    def forward(self, x):
        """
        Forward propagation of the neural network
        :param x: The input to the neural network
        :return: Discriminator logits; the output of the neural network
        """
        # define feedforward behavior
        x = F.leaky_relu(self.batch_norm1(self.conv1(x)), 0.2)
        x = F.leaky_relu(self.batch_norm2(self.conv2(x)), 0.2)
        x = F.leaky_relu(self.batch_norm3(self.conv3(x)), 0.2)
```

```

x = F.leaky_relu(self.batch_norm4(self.conv4(x)), 0.2)
x = self.conv5(x)
# flatten
x = x.view(-1, self.conv_dim*4*4)
# final output layer
x = F.sigmoid(self.fc(x))
return x

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

tests.test_discriminator(Discriminator)

```

Tests Passed

```

/home/andreili/anaconda3/envs/project_2/lib/python3.7/site-packages/torch/nn/functional.py:133:
  warnings.warn("nn.functional.sigmoid is deprecated. Use torch.sigmoid instead.")

```

2.2 Generator

The generator should upsample an input and generate a *new* image of the same size as our training data 32x32x3. This should be mostly transpose convolutional layers with normalization applied to the outputs.

Exercise: Complete the Generator class

- The inputs to the generator are vectors of some length `z_size`
- The output should be a image of shape 32x32x3

In [10]: `class Generator(nn.Module):`

```

def __init__(self, z_size, conv_dim):
    """
    Initialize the Generator Module
    :param z_size: The length of the input latent vector, z
    :param conv_dim: The depth of the inputs to the *last* transpose convolutional layer
    """
    super(Generator, self).__init__()

    # complete init function
    self.conv_dim = conv_dim
    self.t_conv1 = nn.ConvTranspose2d(conv_dim, conv_dim*8, kernel_size=4, stride=2)
    self.batch_norm1 = nn.BatchNorm2d(conv_dim*8)
    self.t_conv2 = nn.ConvTranspose2d(conv_dim*8, conv_dim*4, kernel_size=4, stride=2)
    self.batch_norm2 = nn.BatchNorm2d(conv_dim*4)
    self.t_conv3 = nn.ConvTranspose2d(conv_dim*4, conv_dim*2, kernel_size=4, stride=2)

```

```

self.batch_norm3 = nn.BatchNorm2d(conv_dim*2)
self.t_conv4 = nn.ConvTranspose2d(conv_dim*2, 3, kernel_size=4, stride=2, padding=1)
self.fc = nn.Linear(z_size, conv_dim*4)
print('z_size', z_size)

```

```

def forward(self, x):
    """
    Forward propagation of the neural network
    :param x: The input to the neural network
    :return: A 32x32x3 Tensor image as output
    """
    # define feedforward behavior
    batch_s = x.shape[0]
    x = self.fc(x)
    x = x.view(batch_s, self.conv_dim, 2, 2)
    x = F.relu(self.batch_norm1(self.t_conv1(x)))
    x = F.relu(self.batch_norm2(self.t_conv2(x)))
    x = F.relu(self.batch_norm3(self.t_conv3(x)))
    x = self.t_conv4(x)
    x = F.tanh(x)

    return x

    """
    DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
    """

tests.test_generator(Generator)

```

z_size 25
Tests Passed

```

/home/andreili/anaconda3/envs/project_2/lib/python3.7/site-packages/torch/nn/functional.py:1320:
  warnings.warn("nn.functional.tanh is deprecated. Use torch.tanh instead.")

```

2.3 Initialize the weights of your networks

To help your models converge, you should initialize the weights of the convolutional and linear layers in your model. From reading the [original DCGAN paper](#), they say: > All weights were initialized from a zero-centered Normal distribution with standard deviation 0.02.

So, your next task will be to define a weight initialization function that does just this!

You can refer back to the lesson on weight initialization or even consult existing model code, such as that from [the networks.py file in CycleGAN Github repository](#) to help you complete this function.

Exercise: Complete the weight initialization function

- This should initialize only **convolutional** and **linear** layers
- Initialize the weights to a normal distribution, centered around 0, with a standard deviation of 0.02.
- The bias terms, if they exist, may be left alone or set to 0.

```
In [11]: def weights_init_normal(m):
        """
        Applies initial weights to certain layers in a model .
        The weights are taken from a normal distribution
        with mean = 0, std dev = 0.02.
        :param m: A module or layer in a network
        """
        # classname will be something like:
        # `Conv`, `BatchNorm2d`, `Linear`, etc.
        classname = m.__class__.__name__

        # TODO: Apply initial weights to convolutional and linear layers
        if hasattr(m, 'weight') and (classname.find('Conv') != -1 or classname.find('Linear') != -1):
            nn.init.normal_(m.weight.data, 0.0, 0.02)
            if hasattr(m, 'bias') and m.bias is not None:
                nn.init.constant_(m.bias.data, 0.0)
```

2.4 Build complete network

Define your models' hyperparameters and instantiate the discriminator and generator from the classes defined above. Make sure you've passed in the correct input arguments.

```
In [12]: """
        DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
        """
        def build_network(d_conv_dim, g_conv_dim, z_size):
            # define discriminator and generator
            D = Discriminator(d_conv_dim)
            G = Generator(z_size=z_size, conv_dim=g_conv_dim)

            # initialize model weights
            D.apply(weights_init_normal)
            G.apply(weights_init_normal)

            print(D)
            print()
            print(G)

            return D, G
```


Exercise: Define model hyperparameters

```
In [13]: # Define model hyperparams
```

```
    d_conv_dim = 32
```

```
    g_conv_dim = 32
```

```
    z_size = 100
```

```
    """
```

```
    DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
```

```
    """
```

```
    D, G = build_network(d_conv_dim, g_conv_dim, z_size)
```

```
z_size 100
```

```
Discriminator(
```

```
    (conv1): Conv2d(3, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (batch_norm1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (conv2): Conv2d(32, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (batch_norm2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (conv3): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (batch_norm3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (conv4): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (batch_norm4): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (conv5): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (fc): Linear(in_features=512, out_features=1, bias=True)
```

```
)
```

```
Generator(
```

```
    (t_conv1): ConvTranspose2d(32, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=True)
```

```
    (batch_norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (t_conv2): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=True)
```

```
    (batch_norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (t_conv3): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=True)
```

```
    (batch_norm3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
    (t_conv4): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
```

```
    (fc): Linear(in_features=100, out_features=128, bias=True)
```

```
)
```

2.4.1 Training on GPU

Check if you can train on GPU. Here, we'll set this as a boolean variable `train_on_gpu`. Later, you'll be responsible for making sure that `> * Models, * Model inputs, and * Loss function arguments`

Are moved to GPU, where appropriate.

```
In [14]: """
```

```
    DON'T MODIFY ANYTHING IN THIS CELL
```

```
    """
```

```
    import torch
```

```

# Check for a GPU
train_on_gpu = torch.cuda.is_available()
if not train_on_gpu:
    print('No GPU found. Please use a GPU to train your neural network.')
else:
    print('Training on GPU!')

```

Training on GPU!

2.5 Discriminator and Generator Losses

Now we need to calculate the losses for both types of adversarial networks.

2.5.1 Discriminator Losses

- For the discriminator, the total loss is the sum of the losses for real and fake images, $d_loss = d_real_loss + d_fake_loss$.
- Remember that we want the discriminator to output 1 for real images and 0 for fake images, so we need to set up the losses to reflect that.

2.5.2 Generator Loss

The generator loss will look similar only with flipped labels. The generator's goal is to get the discriminator to *think* its generated images are *real*.

Exercise: Complete real and fake loss functions You may choose to use either cross entropy or a least squares error loss to complete the following `real_loss` and `fake_loss` functions.

```

In [15]: import random
def real_loss(D_out, smooth=False):
    batch_size = D_out.size(0)
    # label smoothing
    if smooth:
        # smooth, real labels = 0.9
        labels = torch.ones(batch_size)*0.9
    else:
        labels = torch.ones(batch_size) # real labels = 1
    # move labels to GPU if available
    if train_on_gpu:
        labels = labels.cuda()
    # binary cross entropy with logits loss
    criterion = nn.BCELoss()
    # calculate loss
    loss = criterion(D_out.squeeze(), labels)
    return loss

```

```
def fake_loss(D_out):
    batch_size = D_out.size(0)
    labels = torch.zeros(batch_size)
    if train_on_gpu:
        labels = labels.cuda()
    criterion = nn.BCELoss()
    # calculate loss
    loss = criterion(D_out.squeeze(), labels)
    return loss
```

2.6 Optimizers

Exercise: Define optimizers for your Discriminator (D) and Generator (G) Define optimizers for your models with appropriate hyperparameters.

In [16]: `import torch.optim as optim`

```
lr=0.0005
g_optimizer = optim.Adam(G.parameters(), lr=lr, betas=(0.3, 0.999))
d_optimizer = optim.Adam(D.parameters(), lr=lr, betas=(0.3, 0.999))
```

2.7 Training

Training will involve alternating between training the discriminator and the generator. You'll use your functions `real_loss` and `fake_loss` to help you calculate the discriminator losses.

- You should train the discriminator by alternating on real and fake images
- Then the generator, which tries to trick the discriminator and should have an opposing loss function

Saving Samples You've been given some code to print out some loss statistics and save some generated "fake" samples.

Exercise: Complete the training function Keep in mind that, if you've moved your models to GPU, you'll also have to move any model inputs to GPU.

```
In [17]: def train(D, G, n_epochs, print_every=50):
    '''Trains adversarial networks for some number of epochs
    param, D: the discriminator network
    param, G: the generator network
    param, n_epochs: number of epochs to train for
    param, print_every: when to print and record the models' losses
    return: D and G losses'''

    # move models to GPU
```

```

if train_on_gpu:
    D.cuda()
    G.cuda()

# keep track of loss and generated, "fake" samples
samples = []
losses = []

# Get some fixed data for sampling. These are images that are held
# constant throughout training, and allow us to inspect the model's performance
sample_size=16
fixed_z = np.random.uniform(-1, 1, size=(sample_size, z_size))
fixed_z = torch.from_numpy(fixed_z).float()
# move z to GPU if available
if train_on_gpu:
    fixed_z = fixed_z.cuda()

# epoch training loop
for epoch in range(n_epochs):

    # batch training loop
    for batch_i, (real_images, _) in enumerate(celeba_train_loader):

        batch_size = real_images.size(0)
        real_images = scale(real_images)

        # =====
        #          YOUR CODE HERE: TRAIN THE NETWORKS
        # =====
        # 1. Train the discriminator on real and fake images
        if train_on_gpu:
            real_images = real_images.cuda()
            d_optimizer.zero_grad()
            D_real = D(real_images)
            d_real_loss = real_loss(D_real)
            z_flex = np.random.uniform(-1, 1, size=(batch_size, z_size))
            z_flex = torch.from_numpy(z_flex).float()
            if train_on_gpu:
                z_flex = z_flex.cuda()

            fake_images = G(z_flex)
            D_fake = D(fake_images)
            d_fake_loss = fake_loss(D_fake)

            d_loss = d_real_loss + d_fake_loss
            d_loss.backward()
            d_optimizer.step()

```

```

# d_loss =

# 2. Train the generator with an adversarial loss
g_optimizer.zero_grad()
z_flex = np.random.uniform(-1, 1, size=(batch_size, z_size))
z_flex = torch.from_numpy(z_flex).float()
if train_on_gpu:
    z_flex = z_flex.cuda()
fake_images = G(z_flex)
D_fake = D(fake_images)
g_loss = real_loss(D_fake, True) # use real loss to flip labels
g_loss.backward()
g_optimizer.step()

# g_loss =

# =====
#                               END OF YOUR CODE
# =====

# Print some loss stats
if batch_i % print_every == 0:
    # append discriminator loss and generator loss
    losses.append((d_loss.item(), g_loss.item()))
    # print discriminator and generator loss
    print('Epoch [{:5d}/{:5d}] | d_loss: {:.4f} | g_loss: {:.4f}'.format(
        epoch+1, n_epochs, d_loss.item(), g_loss.item()))

## AFTER EACH EPOCH##
# this code assumes your generator is named G, feel free to change the name
# generate and save sample, fake images
G.eval() # for generating samples
samples_z = G(fixed_z)
samples.append(samples_z)
G.train() # back to training mode

# Save training generator samples
with open('train_samples.pkl', 'wb') as f:
    pickle.dump(samples, f)

# finally return losses
return losses

```

Set your number of training epochs and train your GAN!

In [18]: # set number of epochs

```
n_epochs = 10
```

```
"""
```

```
DON'T MODIFY ANYTHING IN THIS CELL
```

```
"""
```

```
# call training function
```

```
losses = train(D, G, n_epochs=n_epochs)
```

```
Epoch [ 1/ 10] | d_loss: 1.4103 | g_loss: 0.8649
Epoch [ 1/ 10] | d_loss: 0.6414 | g_loss: 1.8388
Epoch [ 1/ 10] | d_loss: 1.1389 | g_loss: 1.8941
Epoch [ 1/ 10] | d_loss: 1.1434 | g_loss: 1.2447
Epoch [ 1/ 10] | d_loss: 1.2076 | g_loss: 1.2821
Epoch [ 1/ 10] | d_loss: 1.0673 | g_loss: 1.2187
Epoch [ 1/ 10] | d_loss: 1.2883 | g_loss: 1.6798
Epoch [ 1/ 10] | d_loss: 1.1828 | g_loss: 1.2983
Epoch [ 1/ 10] | d_loss: 1.2991 | g_loss: 1.2679
Epoch [ 1/ 10] | d_loss: 1.2314 | g_loss: 1.2728
Epoch [ 1/ 10] | d_loss: 1.0985 | g_loss: 1.7925
Epoch [ 1/ 10] | d_loss: 1.1944 | g_loss: 1.4801
Epoch [ 1/ 10] | d_loss: 1.2610 | g_loss: 1.2265
Epoch [ 1/ 10] | d_loss: 1.1630 | g_loss: 1.1105
Epoch [ 1/ 10] | d_loss: 1.2768 | g_loss: 1.6052
Epoch [ 1/ 10] | d_loss: 1.4771 | g_loss: 0.9836
Epoch [ 1/ 10] | d_loss: 1.1540 | g_loss: 1.0357
Epoch [ 1/ 10] | d_loss: 1.1258 | g_loss: 1.0343
Epoch [ 1/ 10] | d_loss: 1.1666 | g_loss: 1.4473
Epoch [ 1/ 10] | d_loss: 1.0558 | g_loss: 1.3700
Epoch [ 1/ 10] | d_loss: 0.9981 | g_loss: 1.9013
Epoch [ 1/ 10] | d_loss: 1.1576 | g_loss: 1.2420
Epoch [ 1/ 10] | d_loss: 1.3664 | g_loss: 1.2148
Epoch [ 1/ 10] | d_loss: 1.1972 | g_loss: 1.1748
Epoch [ 1/ 10] | d_loss: 1.1513 | g_loss: 0.8498
Epoch [ 1/ 10] | d_loss: 1.2951 | g_loss: 1.3923
Epoch [ 1/ 10] | d_loss: 1.5302 | g_loss: 1.2818
Epoch [ 1/ 10] | d_loss: 0.9914 | g_loss: 1.0479
Epoch [ 1/ 10] | d_loss: 1.9384 | g_loss: 1.7003
Epoch [ 1/ 10] | d_loss: 1.1495 | g_loss: 1.2644
Epoch [ 1/ 10] | d_loss: 1.1185 | g_loss: 1.4582
Epoch [ 1/ 10] | d_loss: 1.1669 | g_loss: 1.3153
Epoch [ 1/ 10] | d_loss: 1.2612 | g_loss: 2.0806
Epoch [ 1/ 10] | d_loss: 1.2118 | g_loss: 1.6748
Epoch [ 1/ 10] | d_loss: 1.1576 | g_loss: 1.3622
Epoch [ 1/ 10] | d_loss: 1.1168 | g_loss: 1.4827
Epoch [ 1/ 10] | d_loss: 0.9562 | g_loss: 1.0371
Epoch [ 1/ 10] | d_loss: 1.5098 | g_loss: 0.5003
Epoch [ 1/ 10] | d_loss: 0.9341 | g_loss: 1.4543
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Epoch [1/	10]	d_loss: 1.3392	g_loss: 1.3947
Epoch [1/	10]	d_loss: 1.6228	g_loss: 2.3628
Epoch [1/	10]	d_loss: 1.5827	g_loss: 0.8523
Epoch [1/	10]	d_loss: 0.9741	g_loss: 1.8089
Epoch [1/	10]	d_loss: 1.0552	g_loss: 2.1223
Epoch [1/	10]	d_loss: 1.4489	g_loss: 1.4104
Epoch [1/	10]	d_loss: 1.1968	g_loss: 1.1674
Epoch [1/	10]	d_loss: 1.0700	g_loss: 1.3904
Epoch [1/	10]	d_loss: 1.3905	g_loss: 1.6217
Epoch [1/	10]	d_loss: 1.0504	g_loss: 1.3312
Epoch [1/	10]	d_loss: 1.1043	g_loss: 1.6325
Epoch [1/	10]	d_loss: 1.3049	g_loss: 1.2405
Epoch [1/	10]	d_loss: 1.2886	g_loss: 1.3083
Epoch [1/	10]	d_loss: 1.1425	g_loss: 1.2979
Epoch [1/	10]	d_loss: 1.0488	g_loss: 1.3812
Epoch [1/	10]	d_loss: 0.9276	g_loss: 0.8432
Epoch [1/	10]	d_loss: 1.3014	g_loss: 1.4298
Epoch [1/	10]	d_loss: 1.0979	g_loss: 1.3750
Epoch [1/	10]	d_loss: 0.7403	g_loss: 1.7325
Epoch [1/	10]	d_loss: 1.4448	g_loss: 1.7976
Epoch [1/	10]	d_loss: 1.7891	g_loss: 1.0492
Epoch [1/	10]	d_loss: 1.3961	g_loss: 1.1867
Epoch [1/	10]	d_loss: 1.3773	g_loss: 0.9567
Epoch [1/	10]	d_loss: 1.3288	g_loss: 1.3316
Epoch [1/	10]	d_loss: 0.9886	g_loss: 1.0417
Epoch [1/	10]	d_loss: 0.8201	g_loss: 1.4480
Epoch [1/	10]	d_loss: 1.2818	g_loss: 0.6758
Epoch [1/	10]	d_loss: 1.2403	g_loss: 1.0661
Epoch [1/	10]	d_loss: 0.9163	g_loss: 1.9001
Epoch [1/	10]	d_loss: 1.1919	g_loss: 1.2016
Epoch [1/	10]	d_loss: 1.7347	g_loss: 1.7580
Epoch [1/	10]	d_loss: 0.8974	g_loss: 1.3421
Epoch [1/	10]	d_loss: 1.2814	g_loss: 0.9780
Epoch [1/	10]	d_loss: 1.2508	g_loss: 1.2255
Epoch [1/	10]	d_loss: 0.7616	g_loss: 0.9957
Epoch [1/	10]	d_loss: 0.9434	g_loss: 2.1051
Epoch [1/	10]	d_loss: 1.2861	g_loss: 1.4068
Epoch [1/	10]	d_loss: 1.5539	g_loss: 1.8186
Epoch [1/	10]	d_loss: 0.8659	g_loss: 2.5097
Epoch [1/	10]	d_loss: 1.0512	g_loss: 1.2382
Epoch [1/	10]	d_loss: 1.2701	g_loss: 0.9436
Epoch [1/	10]	d_loss: 1.1061	g_loss: 0.9417
Epoch [1/	10]	d_loss: 1.3371	g_loss: 1.0656
Epoch [1/	10]	d_loss: 1.0658	g_loss: 1.6086
Epoch [1/	10]	d_loss: 1.1587	g_loss: 1.1787
Epoch [1/	10]	d_loss: 1.1968	g_loss: 1.3910
Epoch [1/	10]	d_loss: 1.7940	g_loss: 0.7069
Epoch [1/	10]	d_loss: 1.1566	g_loss: 1.0682

Epoch [1/	10]	d_loss: 1.1032	g_loss: 1.1307
Epoch [1/	10]	d_loss: 1.0429	g_loss: 1.1458
Epoch [1/	10]	d_loss: 1.4239	g_loss: 1.7134
Epoch [1/	10]	d_loss: 0.9672	g_loss: 1.9387
Epoch [1/	10]	d_loss: 0.9789	g_loss: 1.3274
Epoch [1/	10]	d_loss: 1.0007	g_loss: 1.2832
Epoch [1/	10]	d_loss: 0.8205	g_loss: 1.0760
Epoch [1/	10]	d_loss: 0.9490	g_loss: 1.0498
Epoch [1/	10]	d_loss: 1.3411	g_loss: 0.9639
Epoch [1/	10]	d_loss: 1.3385	g_loss: 1.0201
Epoch [1/	10]	d_loss: 1.2865	g_loss: 2.0793
Epoch [1/	10]	d_loss: 1.7690	g_loss: 1.8706
Epoch [1/	10]	d_loss: 1.3427	g_loss: 0.6426
Epoch [2/	10]	d_loss: 1.3379	g_loss: 1.4318
Epoch [2/	10]	d_loss: 1.3931	g_loss: 0.7442
Epoch [2/	10]	d_loss: 1.3189	g_loss: 1.5368
Epoch [2/	10]	d_loss: 1.0823	g_loss: 1.1640
Epoch [2/	10]	d_loss: 1.0328	g_loss: 1.3576
Epoch [2/	10]	d_loss: 0.9442	g_loss: 1.1528
Epoch [2/	10]	d_loss: 1.0617	g_loss: 1.4182
Epoch [2/	10]	d_loss: 1.3134	g_loss: 1.1250
Epoch [2/	10]	d_loss: 1.1504	g_loss: 1.2901
Epoch [2/	10]	d_loss: 0.8238	g_loss: 1.6327
Epoch [2/	10]	d_loss: 1.2482	g_loss: 0.8293
Epoch [2/	10]	d_loss: 0.7371	g_loss: 0.9002
Epoch [2/	10]	d_loss: 1.2959	g_loss: 1.5339
Epoch [2/	10]	d_loss: 0.9374	g_loss: 1.5543
Epoch [2/	10]	d_loss: 1.0167	g_loss: 1.7638
Epoch [2/	10]	d_loss: 1.7221	g_loss: 1.5521
Epoch [2/	10]	d_loss: 1.0594	g_loss: 1.1673
Epoch [2/	10]	d_loss: 1.0062	g_loss: 1.4988
Epoch [2/	10]	d_loss: 1.6373	g_loss: 1.3845
Epoch [2/	10]	d_loss: 1.3234	g_loss: 1.5693
Epoch [2/	10]	d_loss: 0.9057	g_loss: 1.7029
Epoch [2/	10]	d_loss: 1.2224	g_loss: 1.0099
Epoch [2/	10]	d_loss: 1.3510	g_loss: 1.5625
Epoch [2/	10]	d_loss: 1.0788	g_loss: 1.4520
Epoch [2/	10]	d_loss: 1.3129	g_loss: 1.1288
Epoch [2/	10]	d_loss: 0.9846	g_loss: 0.9875
Epoch [2/	10]	d_loss: 1.3664	g_loss: 1.3223
Epoch [2/	10]	d_loss: 1.0501	g_loss: 1.4118
Epoch [2/	10]	d_loss: 1.2863	g_loss: 1.0138
Epoch [2/	10]	d_loss: 1.3452	g_loss: 1.2460
Epoch [2/	10]	d_loss: 0.9673	g_loss: 0.9498
Epoch [2/	10]	d_loss: 1.5282	g_loss: 0.9356
Epoch [2/	10]	d_loss: 1.3255	g_loss: 0.9614
Epoch [2/	10]	d_loss: 0.8805	g_loss: 1.4827
Epoch [2/	10]	d_loss: 1.3921	g_loss: 1.4464

Epoch [2/	10]	d_loss: 0.9307	g_loss: 0.6970
Epoch [2/	10]	d_loss: 1.0076	g_loss: 1.2315
Epoch [2/	10]	d_loss: 1.3195	g_loss: 1.4990
Epoch [2/	10]	d_loss: 1.1246	g_loss: 1.1201
Epoch [2/	10]	d_loss: 1.4811	g_loss: 1.5163
Epoch [2/	10]	d_loss: 1.4080	g_loss: 0.7973
Epoch [2/	10]	d_loss: 0.9877	g_loss: 1.4691
Epoch [2/	10]	d_loss: 1.4308	g_loss: 1.8648
Epoch [2/	10]	d_loss: 1.1816	g_loss: 1.4244
Epoch [2/	10]	d_loss: 1.0726	g_loss: 1.4631
Epoch [2/	10]	d_loss: 1.3348	g_loss: 1.5772
Epoch [2/	10]	d_loss: 1.1720	g_loss: 1.4212
Epoch [2/	10]	d_loss: 1.4834	g_loss: 0.9715
Epoch [2/	10]	d_loss: 1.4901	g_loss: 2.5980
Epoch [2/	10]	d_loss: 0.9624	g_loss: 1.0663
Epoch [2/	10]	d_loss: 0.8093	g_loss: 0.7809
Epoch [2/	10]	d_loss: 1.1857	g_loss: 1.2683
Epoch [2/	10]	d_loss: 1.0130	g_loss: 1.3367
Epoch [2/	10]	d_loss: 1.1148	g_loss: 1.5311
Epoch [2/	10]	d_loss: 1.3640	g_loss: 0.8682
Epoch [2/	10]	d_loss: 1.1825	g_loss: 1.0035
Epoch [2/	10]	d_loss: 1.1066	g_loss: 0.6622
Epoch [2/	10]	d_loss: 1.1667	g_loss: 1.0609
Epoch [2/	10]	d_loss: 1.5087	g_loss: 1.7658
Epoch [2/	10]	d_loss: 1.3687	g_loss: 0.5061
Epoch [2/	10]	d_loss: 1.1284	g_loss: 1.3343
Epoch [2/	10]	d_loss: 1.7026	g_loss: 1.6096
Epoch [2/	10]	d_loss: 1.0271	g_loss: 0.7906
Epoch [2/	10]	d_loss: 0.9245	g_loss: 0.9155
Epoch [2/	10]	d_loss: 0.8068	g_loss: 1.4053
Epoch [2/	10]	d_loss: 1.1914	g_loss: 1.6554
Epoch [2/	10]	d_loss: 1.8400	g_loss: 1.7792
Epoch [2/	10]	d_loss: 0.9810	g_loss: 1.2477
Epoch [2/	10]	d_loss: 0.9988	g_loss: 1.7551
Epoch [2/	10]	d_loss: 1.1692	g_loss: 1.4613
Epoch [2/	10]	d_loss: 1.2089	g_loss: 1.1251
Epoch [2/	10]	d_loss: 1.0658	g_loss: 1.8237
Epoch [2/	10]	d_loss: 1.1545	g_loss: 2.1184
Epoch [2/	10]	d_loss: 0.8595	g_loss: 1.6110
Epoch [2/	10]	d_loss: 1.1333	g_loss: 0.6485
Epoch [2/	10]	d_loss: 0.9414	g_loss: 1.0437
Epoch [2/	10]	d_loss: 1.2892	g_loss: 1.2252
Epoch [2/	10]	d_loss: 1.5244	g_loss: 1.1650
Epoch [2/	10]	d_loss: 1.6249	g_loss: 1.2196
Epoch [2/	10]	d_loss: 1.5224	g_loss: 1.1750
Epoch [2/	10]	d_loss: 1.1065	g_loss: 1.3608
Epoch [2/	10]	d_loss: 1.1094	g_loss: 1.6201
Epoch [2/	10]	d_loss: 1.1512	g_loss: 1.3448

Epoch [2/	10]	d_loss: 1.0591	g_loss: 1.5769
Epoch [2/	10]	d_loss: 0.8717	g_loss: 1.4261
Epoch [2/	10]	d_loss: 1.1656	g_loss: 1.1680
Epoch [2/	10]	d_loss: 1.0802	g_loss: 1.0869
Epoch [2/	10]	d_loss: 2.1876	g_loss: 0.6316
Epoch [2/	10]	d_loss: 1.3443	g_loss: 1.4422
Epoch [2/	10]	d_loss: 0.9824	g_loss: 0.7092
Epoch [2/	10]	d_loss: 0.9545	g_loss: 1.5944
Epoch [2/	10]	d_loss: 1.0966	g_loss: 1.2372
Epoch [2/	10]	d_loss: 0.7893	g_loss: 1.9092
Epoch [2/	10]	d_loss: 1.5798	g_loss: 0.5473
Epoch [2/	10]	d_loss: 0.9107	g_loss: 0.5006
Epoch [2/	10]	d_loss: 0.7768	g_loss: 0.9963
Epoch [2/	10]	d_loss: 0.9451	g_loss: 1.8689
Epoch [2/	10]	d_loss: 0.9118	g_loss: 0.9094
Epoch [2/	10]	d_loss: 0.9395	g_loss: 0.9856
Epoch [2/	10]	d_loss: 1.5276	g_loss: 2.1160
Epoch [3/	10]	d_loss: 1.1939	g_loss: 0.6975
Epoch [3/	10]	d_loss: 0.8538	g_loss: 1.8723
Epoch [3/	10]	d_loss: 1.0590	g_loss: 1.6050
Epoch [3/	10]	d_loss: 0.8585	g_loss: 1.2536
Epoch [3/	10]	d_loss: 1.1475	g_loss: 1.2481
Epoch [3/	10]	d_loss: 1.0412	g_loss: 1.7288
Epoch [3/	10]	d_loss: 0.8366	g_loss: 1.5531
Epoch [3/	10]	d_loss: 0.9045	g_loss: 1.1366
Epoch [3/	10]	d_loss: 0.9156	g_loss: 1.0974
Epoch [3/	10]	d_loss: 0.9208	g_loss: 2.5555
Epoch [3/	10]	d_loss: 1.1739	g_loss: 1.1167
Epoch [3/	10]	d_loss: 1.1219	g_loss: 1.2061
Epoch [3/	10]	d_loss: 0.9276	g_loss: 0.9949
Epoch [3/	10]	d_loss: 1.0245	g_loss: 0.8370
Epoch [3/	10]	d_loss: 1.2531	g_loss: 0.8387
Epoch [3/	10]	d_loss: 1.0426	g_loss: 1.2204
Epoch [3/	10]	d_loss: 0.9174	g_loss: 1.1708
Epoch [3/	10]	d_loss: 0.9506	g_loss: 1.8751
Epoch [3/	10]	d_loss: 1.1347	g_loss: 1.5218
Epoch [3/	10]	d_loss: 0.7910	g_loss: 1.7509
Epoch [3/	10]	d_loss: 1.6403	g_loss: 0.5896
Epoch [3/	10]	d_loss: 1.0739	g_loss: 1.3162
Epoch [3/	10]	d_loss: 1.9050	g_loss: 0.5380
Epoch [3/	10]	d_loss: 1.4316	g_loss: 0.7644
Epoch [3/	10]	d_loss: 0.7036	g_loss: 1.1737
Epoch [3/	10]	d_loss: 1.0575	g_loss: 1.6897
Epoch [3/	10]	d_loss: 1.1357	g_loss: 1.9642
Epoch [3/	10]	d_loss: 1.0791	g_loss: 1.7353
Epoch [3/	10]	d_loss: 1.2561	g_loss: 1.1281
Epoch [3/	10]	d_loss: 1.3533	g_loss: 0.9836
Epoch [3/	10]	d_loss: 1.1515	g_loss: 0.7911

Epoch [3/	10]		d_loss: 0.8330		g_loss: 0.9250
Epoch [3/	10]		d_loss: 0.9304		g_loss: 0.9170
Epoch [3/	10]		d_loss: 0.8616		g_loss: 1.1445
Epoch [3/	10]		d_loss: 0.9966		g_loss: 1.3215
Epoch [3/	10]		d_loss: 1.5068		g_loss: 1.4020
Epoch [3/	10]		d_loss: 1.3179		g_loss: 1.5114
Epoch [3/	10]		d_loss: 0.8582		g_loss: 1.4847
Epoch [3/	10]		d_loss: 0.9187		g_loss: 0.9491
Epoch [3/	10]		d_loss: 0.7239		g_loss: 1.0730
Epoch [3/	10]		d_loss: 1.1304		g_loss: 1.5026
Epoch [3/	10]		d_loss: 0.6660		g_loss: 1.2360
Epoch [3/	10]		d_loss: 1.2375		g_loss: 1.1830
Epoch [3/	10]		d_loss: 0.8281		g_loss: 1.0219
Epoch [3/	10]		d_loss: 0.7693		g_loss: 1.1429
Epoch [3/	10]		d_loss: 1.1582		g_loss: 1.3646
Epoch [3/	10]		d_loss: 1.2366		g_loss: 1.6084
Epoch [3/	10]		d_loss: 0.8740		g_loss: 1.6241
Epoch [3/	10]		d_loss: 0.9928		g_loss: 0.9537
Epoch [3/	10]		d_loss: 0.8618		g_loss: 1.2965
Epoch [3/	10]		d_loss: 1.2395		g_loss: 0.9222
Epoch [3/	10]		d_loss: 1.0520		g_loss: 1.7028
Epoch [3/	10]		d_loss: 0.8895		g_loss: 0.8827
Epoch [3/	10]		d_loss: 1.0895		g_loss: 0.8075
Epoch [3/	10]		d_loss: 0.9151		g_loss: 0.9287
Epoch [3/	10]		d_loss: 1.0853		g_loss: 0.7727
Epoch [3/	10]		d_loss: 1.7984		g_loss: 2.6502
Epoch [3/	10]		d_loss: 0.6735		g_loss: 1.6411
Epoch [3/	10]		d_loss: 0.8963		g_loss: 1.5371
Epoch [3/	10]		d_loss: 0.8960		g_loss: 0.7179
Epoch [3/	10]		d_loss: 0.8318		g_loss: 0.5750
Epoch [3/	10]		d_loss: 1.1109		g_loss: 1.6622
Epoch [3/	10]		d_loss: 1.6628		g_loss: 1.0108
Epoch [3/	10]		d_loss: 0.7987		g_loss: 1.0814
Epoch [3/	10]		d_loss: 0.7154		g_loss: 1.2933
Epoch [3/	10]		d_loss: 1.0257		g_loss: 1.0376
Epoch [3/	10]		d_loss: 1.0146		g_loss: 1.2451
Epoch [3/	10]		d_loss: 0.9969		g_loss: 1.2037
Epoch [3/	10]		d_loss: 0.7804		g_loss: 0.9637
Epoch [3/	10]		d_loss: 1.3120		g_loss: 0.7019
Epoch [3/	10]		d_loss: 2.0856		g_loss: 2.5503
Epoch [3/	10]		d_loss: 0.9744		g_loss: 1.1674
Epoch [3/	10]		d_loss: 1.9452		g_loss: 0.7028
Epoch [3/	10]		d_loss: 0.8743		g_loss: 1.7334
Epoch [3/	10]		d_loss: 1.6635		g_loss: 0.7133
Epoch [3/	10]		d_loss: 1.6023		g_loss: 2.0029
Epoch [3/	10]		d_loss: 1.0845		g_loss: 2.5748
Epoch [3/	10]		d_loss: 1.1788		g_loss: 0.8825
Epoch [3/	10]		d_loss: 1.0841		g_loss: 0.9637

Epoch [3/	10]	d_loss: 1.0472	g_loss: 1.2540
Epoch [3/	10]	d_loss: 0.6032	g_loss: 1.0978
Epoch [3/	10]	d_loss: 0.9984	g_loss: 1.1032
Epoch [3/	10]	d_loss: 1.1737	g_loss: 1.1946
Epoch [3/	10]	d_loss: 1.1041	g_loss: 3.0604
Epoch [3/	10]	d_loss: 1.1370	g_loss: 0.8613
Epoch [3/	10]	d_loss: 1.8401	g_loss: 1.3623
Epoch [3/	10]	d_loss: 0.7785	g_loss: 2.2317
Epoch [3/	10]	d_loss: 0.6003	g_loss: 1.9250
Epoch [3/	10]	d_loss: 1.0168	g_loss: 1.1982
Epoch [3/	10]	d_loss: 0.5025	g_loss: 1.7267
Epoch [3/	10]	d_loss: 0.6585	g_loss: 1.6590
Epoch [3/	10]	d_loss: 0.9350	g_loss: 1.3754
Epoch [3/	10]	d_loss: 1.3864	g_loss: 1.4820
Epoch [3/	10]	d_loss: 1.1537	g_loss: 1.0857
Epoch [3/	10]	d_loss: 0.7770	g_loss: 1.2987
Epoch [3/	10]	d_loss: 0.6280	g_loss: 1.2153
Epoch [3/	10]	d_loss: 1.1406	g_loss: 1.7510
Epoch [3/	10]	d_loss: 0.9211	g_loss: 1.0967
Epoch [3/	10]	d_loss: 1.4530	g_loss: 1.0076
Epoch [3/	10]	d_loss: 1.0602	g_loss: 1.2380
Epoch [4/	10]	d_loss: 0.9532	g_loss: 1.6827
Epoch [4/	10]	d_loss: 0.9183	g_loss: 1.4903
Epoch [4/	10]	d_loss: 1.2641	g_loss: 0.9632
Epoch [4/	10]	d_loss: 1.2330	g_loss: 2.4446
Epoch [4/	10]	d_loss: 1.1490	g_loss: 2.1710
Epoch [4/	10]	d_loss: 0.7996	g_loss: 0.8543
Epoch [4/	10]	d_loss: 0.9126	g_loss: 2.2447
Epoch [4/	10]	d_loss: 1.3259	g_loss: 1.4373
Epoch [4/	10]	d_loss: 1.2079	g_loss: 0.9897
Epoch [4/	10]	d_loss: 1.3487	g_loss: 1.8678
Epoch [4/	10]	d_loss: 1.2319	g_loss: 1.4863
Epoch [4/	10]	d_loss: 1.7939	g_loss: 1.9478
Epoch [4/	10]	d_loss: 1.0301	g_loss: 1.1384
Epoch [4/	10]	d_loss: 0.7094	g_loss: 1.2593
Epoch [4/	10]	d_loss: 1.2279	g_loss: 0.9519
Epoch [4/	10]	d_loss: 0.7810	g_loss: 1.7262
Epoch [4/	10]	d_loss: 0.8896	g_loss: 1.2655
Epoch [4/	10]	d_loss: 0.8726	g_loss: 1.4518
Epoch [4/	10]	d_loss: 1.0130	g_loss: 1.1444
Epoch [4/	10]	d_loss: 0.6001	g_loss: 2.5749
Epoch [4/	10]	d_loss: 0.8966	g_loss: 1.0271
Epoch [4/	10]	d_loss: 0.8443	g_loss: 2.4946
Epoch [4/	10]	d_loss: 0.6677	g_loss: 2.0419
Epoch [4/	10]	d_loss: 0.8628	g_loss: 1.5613
Epoch [4/	10]	d_loss: 1.4877	g_loss: 1.6583
Epoch [4/	10]	d_loss: 1.2863	g_loss: 0.7654
Epoch [4/	10]	d_loss: 0.5247	g_loss: 2.2302

Epoch [4/	10]	d_loss: 0.4518	g_loss: 1.8348
Epoch [4/	10]	d_loss: 0.5122	g_loss: 2.2591
Epoch [4/	10]	d_loss: 0.9537	g_loss: 1.4999
Epoch [4/	10]	d_loss: 0.9248	g_loss: 1.6518
Epoch [4/	10]	d_loss: 1.0471	g_loss: 1.5773
Epoch [4/	10]	d_loss: 0.4747	g_loss: 1.5146
Epoch [4/	10]	d_loss: 1.0194	g_loss: 1.4899
Epoch [4/	10]	d_loss: 0.9436	g_loss: 0.6121
Epoch [4/	10]	d_loss: 0.8733	g_loss: 1.4771
Epoch [4/	10]	d_loss: 1.3106	g_loss: 1.3174
Epoch [4/	10]	d_loss: 0.7846	g_loss: 1.7301
Epoch [4/	10]	d_loss: 0.9719	g_loss: 1.5384
Epoch [4/	10]	d_loss: 1.2102	g_loss: 1.2036
Epoch [4/	10]	d_loss: 0.5000	g_loss: 2.1715
Epoch [4/	10]	d_loss: 1.2394	g_loss: 1.2792
Epoch [4/	10]	d_loss: 0.9689	g_loss: 1.1481
Epoch [4/	10]	d_loss: 0.8266	g_loss: 1.0324
Epoch [4/	10]	d_loss: 0.8996	g_loss: 2.3515
Epoch [4/	10]	d_loss: 0.8213	g_loss: 0.5968
Epoch [4/	10]	d_loss: 1.8528	g_loss: 2.2124
Epoch [4/	10]	d_loss: 0.6160	g_loss: 2.1925
Epoch [4/	10]	d_loss: 1.0917	g_loss: 2.3224
Epoch [4/	10]	d_loss: 0.7951	g_loss: 0.9747
Epoch [4/	10]	d_loss: 1.0053	g_loss: 2.6722
Epoch [4/	10]	d_loss: 1.0174	g_loss: 1.6424
Epoch [4/	10]	d_loss: 1.5945	g_loss: 1.6615
Epoch [4/	10]	d_loss: 1.4528	g_loss: 0.8363
Epoch [4/	10]	d_loss: 1.6926	g_loss: 2.3870
Epoch [4/	10]	d_loss: 0.8564	g_loss: 0.9154
Epoch [4/	10]	d_loss: 0.9711	g_loss: 1.1711
Epoch [4/	10]	d_loss: 0.8593	g_loss: 1.0469
Epoch [4/	10]	d_loss: 1.1585	g_loss: 1.5057
Epoch [4/	10]	d_loss: 1.2417	g_loss: 1.2665
Epoch [4/	10]	d_loss: 0.6405	g_loss: 0.4508
Epoch [4/	10]	d_loss: 1.0384	g_loss: 0.9953
Epoch [4/	10]	d_loss: 0.7906	g_loss: 1.4927
Epoch [4/	10]	d_loss: 1.0335	g_loss: 1.7483
Epoch [4/	10]	d_loss: 1.1060	g_loss: 1.2970
Epoch [4/	10]	d_loss: 1.2898	g_loss: 2.6675
Epoch [4/	10]	d_loss: 1.3971	g_loss: 0.8059
Epoch [4/	10]	d_loss: 1.1067	g_loss: 1.4219
Epoch [4/	10]	d_loss: 0.6596	g_loss: 1.2327
Epoch [4/	10]	d_loss: 0.9183	g_loss: 1.0875
Epoch [4/	10]	d_loss: 1.2820	g_loss: 1.5328
Epoch [4/	10]	d_loss: 1.0861	g_loss: 1.0447
Epoch [4/	10]	d_loss: 0.8615	g_loss: 1.5066
Epoch [4/	10]	d_loss: 0.9028	g_loss: 1.3933
Epoch [4/	10]	d_loss: 0.7344	g_loss: 1.1209

Epoch [4/	10]	d_loss: 0.5735	g_loss: 0.9192
Epoch [4/	10]	d_loss: 0.8148	g_loss: 1.6641
Epoch [4/	10]	d_loss: 0.8113	g_loss: 1.5773
Epoch [4/	10]	d_loss: 1.2705	g_loss: 1.9547
Epoch [4/	10]	d_loss: 0.4782	g_loss: 1.5067
Epoch [4/	10]	d_loss: 1.2484	g_loss: 2.0060
Epoch [4/	10]	d_loss: 1.3035	g_loss: 1.5368
Epoch [4/	10]	d_loss: 1.5325	g_loss: 0.7558
Epoch [4/	10]	d_loss: 0.8324	g_loss: 1.2056
Epoch [4/	10]	d_loss: 1.0244	g_loss: 1.3175
Epoch [4/	10]	d_loss: 0.7272	g_loss: 1.3613
Epoch [4/	10]	d_loss: 1.3069	g_loss: 2.0744
Epoch [4/	10]	d_loss: 0.7670	g_loss: 1.2373
Epoch [4/	10]	d_loss: 1.1195	g_loss: 1.8027
Epoch [4/	10]	d_loss: 0.9227	g_loss: 1.3825
Epoch [4/	10]	d_loss: 1.7787	g_loss: 2.0837
Epoch [4/	10]	d_loss: 0.7396	g_loss: 1.4075
Epoch [4/	10]	d_loss: 0.9625	g_loss: 2.6159
Epoch [4/	10]	d_loss: 0.8395	g_loss: 1.3581
Epoch [4/	10]	d_loss: 0.8313	g_loss: 2.0187
Epoch [4/	10]	d_loss: 0.8822	g_loss: 1.2271
Epoch [4/	10]	d_loss: 0.6529	g_loss: 2.0047
Epoch [4/	10]	d_loss: 1.3928	g_loss: 1.1244
Epoch [4/	10]	d_loss: 0.8067	g_loss: 1.8966
Epoch [4/	10]	d_loss: 0.8510	g_loss: 1.9897
Epoch [5/	10]	d_loss: 0.9166	g_loss: 0.9109
Epoch [5/	10]	d_loss: 0.5274	g_loss: 1.7477
Epoch [5/	10]	d_loss: 0.5547	g_loss: 2.2752
Epoch [5/	10]	d_loss: 0.8210	g_loss: 0.7183
Epoch [5/	10]	d_loss: 0.4445	g_loss: 2.1942
Epoch [5/	10]	d_loss: 0.7507	g_loss: 1.0824
Epoch [5/	10]	d_loss: 1.3123	g_loss: 0.7929
Epoch [5/	10]	d_loss: 0.9258	g_loss: 0.9372
Epoch [5/	10]	d_loss: 1.9030	g_loss: 1.7763
Epoch [5/	10]	d_loss: 1.4073	g_loss: 2.0853
Epoch [5/	10]	d_loss: 0.5200	g_loss: 1.6764
Epoch [5/	10]	d_loss: 0.5155	g_loss: 0.8750
Epoch [5/	10]	d_loss: 0.4792	g_loss: 2.2765
Epoch [5/	10]	d_loss: 1.0491	g_loss: 1.5939
Epoch [5/	10]	d_loss: 0.9230	g_loss: 0.6559
Epoch [5/	10]	d_loss: 1.0197	g_loss: 1.0866
Epoch [5/	10]	d_loss: 0.9938	g_loss: 1.1983
Epoch [5/	10]	d_loss: 0.7105	g_loss: 1.0754
Epoch [5/	10]	d_loss: 0.7726	g_loss: 1.2404
Epoch [5/	10]	d_loss: 1.1384	g_loss: 0.7565
Epoch [5/	10]	d_loss: 0.6885	g_loss: 1.6991
Epoch [5/	10]	d_loss: 0.9113	g_loss: 1.6230
Epoch [5/	10]	d_loss: 1.3084	g_loss: 0.8324

Epoch [5/	10]	d_loss: 0.5023	g_loss: 2.1223
Epoch [5/	10]	d_loss: 1.7493	g_loss: 1.3027
Epoch [5/	10]	d_loss: 1.1548	g_loss: 0.6824
Epoch [5/	10]	d_loss: 0.8755	g_loss: 1.5680
Epoch [5/	10]	d_loss: 1.0124	g_loss: 1.3306
Epoch [5/	10]	d_loss: 0.7783	g_loss: 2.3941
Epoch [5/	10]	d_loss: 0.9790	g_loss: 1.3543
Epoch [5/	10]	d_loss: 0.4920	g_loss: 1.3563
Epoch [5/	10]	d_loss: 0.4713	g_loss: 2.4572
Epoch [5/	10]	d_loss: 0.7678	g_loss: 1.2969
Epoch [5/	10]	d_loss: 0.8048	g_loss: 1.9051
Epoch [5/	10]	d_loss: 1.3612	g_loss: 1.1191
Epoch [5/	10]	d_loss: 1.4942	g_loss: 0.7424
Epoch [5/	10]	d_loss: 1.6317	g_loss: 1.2699
Epoch [5/	10]	d_loss: 0.4619	g_loss: 1.9289
Epoch [5/	10]	d_loss: 1.1223	g_loss: 1.7001
Epoch [5/	10]	d_loss: 0.8188	g_loss: 0.9223
Epoch [5/	10]	d_loss: 0.7488	g_loss: 0.6590
Epoch [5/	10]	d_loss: 1.0117	g_loss: 1.9842
Epoch [5/	10]	d_loss: 0.6902	g_loss: 1.8735
Epoch [5/	10]	d_loss: 0.8938	g_loss: 1.1908
Epoch [5/	10]	d_loss: 1.3954	g_loss: 0.8841
Epoch [5/	10]	d_loss: 0.7160	g_loss: 2.3099
Epoch [5/	10]	d_loss: 1.0774	g_loss: 3.4963
Epoch [5/	10]	d_loss: 1.1672	g_loss: 0.8723
Epoch [5/	10]	d_loss: 0.6665	g_loss: 2.3460
Epoch [5/	10]	d_loss: 0.6310	g_loss: 1.1578
Epoch [5/	10]	d_loss: 0.5426	g_loss: 1.8361
Epoch [5/	10]	d_loss: 0.6256	g_loss: 1.9651
Epoch [5/	10]	d_loss: 0.7586	g_loss: 1.6411
Epoch [5/	10]	d_loss: 1.0595	g_loss: 1.5612
Epoch [5/	10]	d_loss: 0.7740	g_loss: 0.8654
Epoch [5/	10]	d_loss: 0.7464	g_loss: 1.8950
Epoch [5/	10]	d_loss: 0.5281	g_loss: 0.8100
Epoch [5/	10]	d_loss: 1.2437	g_loss: 0.6387
Epoch [5/	10]	d_loss: 0.9890	g_loss: 2.3341
Epoch [5/	10]	d_loss: 0.6741	g_loss: 1.9735
Epoch [5/	10]	d_loss: 0.9407	g_loss: 1.5267
Epoch [5/	10]	d_loss: 0.6912	g_loss: 0.8558
Epoch [5/	10]	d_loss: 1.0265	g_loss: 2.3864
Epoch [5/	10]	d_loss: 0.7701	g_loss: 0.9044
Epoch [5/	10]	d_loss: 0.4345	g_loss: 1.6829
Epoch [5/	10]	d_loss: 0.6971	g_loss: 3.1617
Epoch [5/	10]	d_loss: 0.6683	g_loss: 2.2199
Epoch [5/	10]	d_loss: 1.2863	g_loss: 1.2639
Epoch [5/	10]	d_loss: 1.0823	g_loss: 2.5284
Epoch [5/	10]	d_loss: 0.7077	g_loss: 1.9231
Epoch [5/	10]	d_loss: 0.6878	g_loss: 1.5830

Epoch [5/	10]	d_loss: 1.4067	g_loss: 1.3835
Epoch [5/	10]	d_loss: 1.0378	g_loss: 2.3387
Epoch [5/	10]	d_loss: 1.6075	g_loss: 2.7685
Epoch [5/	10]	d_loss: 0.8502	g_loss: 1.4110
Epoch [5/	10]	d_loss: 0.9213	g_loss: 2.3204
Epoch [5/	10]	d_loss: 0.5483	g_loss: 1.4494
Epoch [5/	10]	d_loss: 1.3129	g_loss: 3.2201
Epoch [5/	10]	d_loss: 0.3741	g_loss: 3.1199
Epoch [5/	10]	d_loss: 0.9282	g_loss: 2.1041
Epoch [5/	10]	d_loss: 0.7695	g_loss: 2.2916
Epoch [5/	10]	d_loss: 0.4838	g_loss: 1.3339
Epoch [5/	10]	d_loss: 1.0026	g_loss: 1.1537
Epoch [5/	10]	d_loss: 1.0132	g_loss: 1.1944
Epoch [5/	10]	d_loss: 1.4133	g_loss: 1.5574
Epoch [5/	10]	d_loss: 0.7990	g_loss: 1.4073
Epoch [5/	10]	d_loss: 1.0526	g_loss: 1.3659
Epoch [5/	10]	d_loss: 0.9425	g_loss: 0.8701
Epoch [5/	10]	d_loss: 0.5832	g_loss: 3.0287
Epoch [5/	10]	d_loss: 0.3876	g_loss: 0.9847
Epoch [5/	10]	d_loss: 1.7602	g_loss: 1.2398
Epoch [5/	10]	d_loss: 1.5685	g_loss: 2.7442
Epoch [5/	10]	d_loss: 0.7033	g_loss: 0.9335
Epoch [5/	10]	d_loss: 1.2229	g_loss: 1.7393
Epoch [5/	10]	d_loss: 0.9503	g_loss: 1.0868
Epoch [5/	10]	d_loss: 1.1870	g_loss: 1.2888
Epoch [5/	10]	d_loss: 1.0710	g_loss: 1.6763
Epoch [5/	10]	d_loss: 0.7037	g_loss: 3.3399
Epoch [5/	10]	d_loss: 0.9383	g_loss: 2.7474
Epoch [5/	10]	d_loss: 0.7966	g_loss: 1.4184
Epoch [6/	10]	d_loss: 1.7135	g_loss: 1.8710
Epoch [6/	10]	d_loss: 0.9887	g_loss: 2.0725
Epoch [6/	10]	d_loss: 0.7877	g_loss: 0.7019
Epoch [6/	10]	d_loss: 1.1165	g_loss: 0.8605
Epoch [6/	10]	d_loss: 0.5470	g_loss: 1.5494
Epoch [6/	10]	d_loss: 1.8400	g_loss: 1.4453
Epoch [6/	10]	d_loss: 0.4436	g_loss: 3.1697
Epoch [6/	10]	d_loss: 1.5085	g_loss: 0.8224
Epoch [6/	10]	d_loss: 0.7772	g_loss: 2.1140
Epoch [6/	10]	d_loss: 0.5046	g_loss: 1.6985
Epoch [6/	10]	d_loss: 0.4173	g_loss: 2.0933
Epoch [6/	10]	d_loss: 1.0846	g_loss: 1.4411
Epoch [6/	10]	d_loss: 0.9765	g_loss: 1.1312
Epoch [6/	10]	d_loss: 0.6386	g_loss: 2.0008
Epoch [6/	10]	d_loss: 0.6914	g_loss: 1.9655
Epoch [6/	10]	d_loss: 1.5439	g_loss: 1.0561
Epoch [6/	10]	d_loss: 0.8500	g_loss: 1.0383
Epoch [6/	10]	d_loss: 0.7134	g_loss: 2.3271
Epoch [6/	10]	d_loss: 1.8959	g_loss: 1.5858

Epoch [6/	10]	d_loss: 1.8578	g_loss: 0.8888
Epoch [6/	10]	d_loss: 0.9584	g_loss: 0.7639
Epoch [6/	10]	d_loss: 0.3678	g_loss: 1.1231
Epoch [6/	10]	d_loss: 0.6728	g_loss: 2.0519
Epoch [6/	10]	d_loss: 1.5112	g_loss: 0.6726
Epoch [6/	10]	d_loss: 1.2238	g_loss: 2.6889
Epoch [6/	10]	d_loss: 1.1194	g_loss: 1.3246
Epoch [6/	10]	d_loss: 0.5974	g_loss: 3.1711
Epoch [6/	10]	d_loss: 0.6485	g_loss: 1.0877
Epoch [6/	10]	d_loss: 1.1482	g_loss: 1.9406
Epoch [6/	10]	d_loss: 0.7956	g_loss: 1.9278
Epoch [6/	10]	d_loss: 1.1536	g_loss: 2.1339
Epoch [6/	10]	d_loss: 0.5177	g_loss: 2.0163
Epoch [6/	10]	d_loss: 1.0867	g_loss: 1.5767
Epoch [6/	10]	d_loss: 0.7795	g_loss: 1.5803
Epoch [6/	10]	d_loss: 0.7052	g_loss: 1.0140
Epoch [6/	10]	d_loss: 0.9675	g_loss: 1.4741
Epoch [6/	10]	d_loss: 0.5911	g_loss: 1.4588
Epoch [6/	10]	d_loss: 0.6503	g_loss: 2.1733
Epoch [6/	10]	d_loss: 0.6057	g_loss: 2.2397
Epoch [6/	10]	d_loss: 0.3294	g_loss: 2.6504
Epoch [6/	10]	d_loss: 0.7181	g_loss: 1.7079
Epoch [6/	10]	d_loss: 0.9719	g_loss: 2.2286
Epoch [6/	10]	d_loss: 1.0388	g_loss: 1.5492
Epoch [6/	10]	d_loss: 0.9217	g_loss: 1.2295
Epoch [6/	10]	d_loss: 0.9972	g_loss: 2.5132
Epoch [6/	10]	d_loss: 0.8831	g_loss: 2.3872
Epoch [6/	10]	d_loss: 1.4501	g_loss: 2.1100
Epoch [6/	10]	d_loss: 0.7529	g_loss: 1.1389
Epoch [6/	10]	d_loss: 0.5522	g_loss: 2.7998
Epoch [6/	10]	d_loss: 1.4511	g_loss: 2.3681
Epoch [6/	10]	d_loss: 0.9207	g_loss: 1.8509
Epoch [6/	10]	d_loss: 1.0050	g_loss: 2.5140
Epoch [6/	10]	d_loss: 1.9369	g_loss: 1.9291
Epoch [6/	10]	d_loss: 0.6214	g_loss: 1.3777
Epoch [6/	10]	d_loss: 0.6676	g_loss: 1.2284
Epoch [6/	10]	d_loss: 0.9400	g_loss: 1.0463
Epoch [6/	10]	d_loss: 0.7218	g_loss: 2.0530
Epoch [6/	10]	d_loss: 1.0717	g_loss: 1.9356
Epoch [6/	10]	d_loss: 1.3256	g_loss: 1.3650
Epoch [6/	10]	d_loss: 0.9959	g_loss: 1.0122
Epoch [6/	10]	d_loss: 1.0244	g_loss: 0.9735
Epoch [6/	10]	d_loss: 0.6719	g_loss: 1.7960
Epoch [6/	10]	d_loss: 0.7088	g_loss: 1.9801
Epoch [6/	10]	d_loss: 0.6638	g_loss: 1.5116
Epoch [6/	10]	d_loss: 0.8131	g_loss: 2.7799
Epoch [6/	10]	d_loss: 0.4599	g_loss: 1.6609
Epoch [6/	10]	d_loss: 0.5289	g_loss: 2.1029

Epoch [6/	10]	d_loss: 0.3911	g_loss: 1.8151
Epoch [6/	10]	d_loss: 0.9728	g_loss: 2.3865
Epoch [6/	10]	d_loss: 1.4331	g_loss: 3.1804
Epoch [6/	10]	d_loss: 1.7477	g_loss: 1.9537
Epoch [6/	10]	d_loss: 0.3743	g_loss: 2.4501
Epoch [6/	10]	d_loss: 1.4811	g_loss: 1.0417
Epoch [6/	10]	d_loss: 1.6020	g_loss: 1.2445
Epoch [6/	10]	d_loss: 0.8938	g_loss: 1.9133
Epoch [6/	10]	d_loss: 0.4381	g_loss: 0.5416
Epoch [6/	10]	d_loss: 0.6358	g_loss: 2.3125
Epoch [6/	10]	d_loss: 0.5751	g_loss: 1.2688
Epoch [6/	10]	d_loss: 0.7420	g_loss: 1.5336
Epoch [6/	10]	d_loss: 1.0336	g_loss: 2.1683
Epoch [6/	10]	d_loss: 0.8788	g_loss: 0.7717
Epoch [6/	10]	d_loss: 0.9776	g_loss: 1.0694
Epoch [6/	10]	d_loss: 0.9040	g_loss: 1.4337
Epoch [6/	10]	d_loss: 1.1538	g_loss: 1.1800
Epoch [6/	10]	d_loss: 0.4627	g_loss: 2.2263
Epoch [6/	10]	d_loss: 0.9503	g_loss: 2.6689
Epoch [6/	10]	d_loss: 0.4158	g_loss: 1.6264
Epoch [6/	10]	d_loss: 1.1428	g_loss: 2.1964
Epoch [6/	10]	d_loss: 0.9313	g_loss: 2.2854
Epoch [6/	10]	d_loss: 1.1153	g_loss: 1.6482
Epoch [6/	10]	d_loss: 1.0487	g_loss: 1.1411
Epoch [6/	10]	d_loss: 1.3513	g_loss: 1.8494
Epoch [6/	10]	d_loss: 0.9619	g_loss: 1.3019
Epoch [6/	10]	d_loss: 1.5933	g_loss: 1.0450
Epoch [6/	10]	d_loss: 0.4145	g_loss: 1.3245
Epoch [6/	10]	d_loss: 0.9160	g_loss: 0.6952
Epoch [6/	10]	d_loss: 0.7498	g_loss: 1.3424
Epoch [6/	10]	d_loss: 0.5712	g_loss: 1.8602
Epoch [6/	10]	d_loss: 1.1057	g_loss: 1.5860
Epoch [6/	10]	d_loss: 0.3822	g_loss: 0.9132
Epoch [7/	10]	d_loss: 0.7271	g_loss: 1.6217
Epoch [7/	10]	d_loss: 0.7827	g_loss: 0.6475
Epoch [7/	10]	d_loss: 1.2350	g_loss: 1.7717
Epoch [7/	10]	d_loss: 1.2344	g_loss: 1.8899
Epoch [7/	10]	d_loss: 1.0409	g_loss: 0.7569
Epoch [7/	10]	d_loss: 0.9128	g_loss: 1.0516
Epoch [7/	10]	d_loss: 0.5883	g_loss: 2.0602
Epoch [7/	10]	d_loss: 0.4755	g_loss: 1.8545
Epoch [7/	10]	d_loss: 1.7880	g_loss: 2.1898
Epoch [7/	10]	d_loss: 1.1128	g_loss: 2.2575
Epoch [7/	10]	d_loss: 1.0296	g_loss: 1.5661
Epoch [7/	10]	d_loss: 1.3867	g_loss: 1.5386
Epoch [7/	10]	d_loss: 1.4130	g_loss: 1.7142
Epoch [7/	10]	d_loss: 1.6220	g_loss: 2.7156
Epoch [7/	10]	d_loss: 1.0585	g_loss: 1.7828

Epoch [7/	10]	d_loss: 0.2785	g_loss: 1.3857
Epoch [7/	10]	d_loss: 0.7628	g_loss: 2.1358
Epoch [7/	10]	d_loss: 0.4366	g_loss: 0.9935
Epoch [7/	10]	d_loss: 1.3216	g_loss: 1.2990
Epoch [7/	10]	d_loss: 1.0972	g_loss: 2.9182
Epoch [7/	10]	d_loss: 1.1646	g_loss: 1.5439
Epoch [7/	10]	d_loss: 1.4908	g_loss: 1.0536
Epoch [7/	10]	d_loss: 0.7951	g_loss: 1.2971
Epoch [7/	10]	d_loss: 0.9910	g_loss: 3.5327
Epoch [7/	10]	d_loss: 0.7094	g_loss: 1.2395
Epoch [7/	10]	d_loss: 1.8504	g_loss: 1.4879
Epoch [7/	10]	d_loss: 0.6332	g_loss: 2.1100
Epoch [7/	10]	d_loss: 0.8184	g_loss: 3.0048
Epoch [7/	10]	d_loss: 0.9481	g_loss: 1.4509
Epoch [7/	10]	d_loss: 1.3892	g_loss: 1.4813
Epoch [7/	10]	d_loss: 0.4275	g_loss: 1.7704
Epoch [7/	10]	d_loss: 1.8681	g_loss: 2.8185
Epoch [7/	10]	d_loss: 0.9678	g_loss: 0.8730
Epoch [7/	10]	d_loss: 0.9722	g_loss: 2.7843
Epoch [7/	10]	d_loss: 0.8836	g_loss: 2.4510
Epoch [7/	10]	d_loss: 0.8343	g_loss: 1.9504
Epoch [7/	10]	d_loss: 0.8136	g_loss: 1.6529
Epoch [7/	10]	d_loss: 1.5739	g_loss: 0.7590
Epoch [7/	10]	d_loss: 0.6997	g_loss: 1.1344
Epoch [7/	10]	d_loss: 0.4370	g_loss: 1.9532
Epoch [7/	10]	d_loss: 0.6037	g_loss: 1.8138
Epoch [7/	10]	d_loss: 0.5307	g_loss: 2.5431
Epoch [7/	10]	d_loss: 1.1014	g_loss: 1.7913
Epoch [7/	10]	d_loss: 0.6164	g_loss: 0.9741
Epoch [7/	10]	d_loss: 0.5860	g_loss: 1.0301
Epoch [7/	10]	d_loss: 1.0810	g_loss: 1.2147
Epoch [7/	10]	d_loss: 0.4272	g_loss: 1.4698
Epoch [7/	10]	d_loss: 1.0323	g_loss: 2.2823
Epoch [7/	10]	d_loss: 0.9049	g_loss: 1.7446
Epoch [7/	10]	d_loss: 0.9012	g_loss: 1.2777
Epoch [7/	10]	d_loss: 1.2145	g_loss: 1.2961
Epoch [7/	10]	d_loss: 0.6243	g_loss: 2.4842
Epoch [7/	10]	d_loss: 0.8566	g_loss: 2.6523
Epoch [7/	10]	d_loss: 0.6723	g_loss: 1.5318
Epoch [7/	10]	d_loss: 0.5809	g_loss: 1.6777
Epoch [7/	10]	d_loss: 0.7234	g_loss: 1.8118
Epoch [7/	10]	d_loss: 1.0768	g_loss: 1.3019
Epoch [7/	10]	d_loss: 0.2490	g_loss: 2.1094
Epoch [7/	10]	d_loss: 0.8475	g_loss: 1.6520
Epoch [7/	10]	d_loss: 0.5549	g_loss: 1.8005
Epoch [7/	10]	d_loss: 1.3352	g_loss: 1.1700
Epoch [7/	10]	d_loss: 0.8281	g_loss: 1.4018
Epoch [7/	10]	d_loss: 0.9985	g_loss: 2.7314

Epoch [7/	10]	d_loss: 1.1129	g_loss: 1.2226
Epoch [7/	10]	d_loss: 1.2877	g_loss: 3.1141
Epoch [7/	10]	d_loss: 1.0375	g_loss: 2.3318
Epoch [7/	10]	d_loss: 0.7099	g_loss: 1.2404
Epoch [7/	10]	d_loss: 0.8821	g_loss: 1.0305
Epoch [7/	10]	d_loss: 0.5517	g_loss: 0.8410
Epoch [7/	10]	d_loss: 1.1531	g_loss: 1.7852
Epoch [7/	10]	d_loss: 0.9795	g_loss: 2.2440
Epoch [7/	10]	d_loss: 1.4185	g_loss: 3.6400
Epoch [7/	10]	d_loss: 1.5970	g_loss: 1.5769
Epoch [7/	10]	d_loss: 0.6078	g_loss: 2.7808
Epoch [7/	10]	d_loss: 0.8604	g_loss: 1.4773
Epoch [7/	10]	d_loss: 0.2924	g_loss: 2.0738
Epoch [7/	10]	d_loss: 1.0308	g_loss: 1.5060
Epoch [7/	10]	d_loss: 0.7151	g_loss: 0.9210
Epoch [7/	10]	d_loss: 0.6067	g_loss: 1.7722
Epoch [7/	10]	d_loss: 1.1525	g_loss: 1.2840
Epoch [7/	10]	d_loss: 0.4157	g_loss: 2.5741
Epoch [7/	10]	d_loss: 0.7669	g_loss: 1.1074
Epoch [7/	10]	d_loss: 0.4336	g_loss: 2.8630
Epoch [7/	10]	d_loss: 0.5781	g_loss: 1.3904
Epoch [7/	10]	d_loss: 0.5227	g_loss: 1.0615
Epoch [7/	10]	d_loss: 1.3942	g_loss: 3.0023
Epoch [7/	10]	d_loss: 0.7205	g_loss: 2.1578
Epoch [7/	10]	d_loss: 0.5515	g_loss: 1.7875
Epoch [7/	10]	d_loss: 0.4051	g_loss: 1.9601
Epoch [7/	10]	d_loss: 0.3578	g_loss: 1.7808
Epoch [7/	10]	d_loss: 0.3140	g_loss: 2.0839
Epoch [7/	10]	d_loss: 0.7981	g_loss: 1.4898
Epoch [7/	10]	d_loss: 1.2857	g_loss: 2.4852
Epoch [7/	10]	d_loss: 1.8538	g_loss: 1.2343
Epoch [7/	10]	d_loss: 0.7544	g_loss: 1.0284
Epoch [7/	10]	d_loss: 0.9640	g_loss: 1.1378
Epoch [7/	10]	d_loss: 0.8477	g_loss: 3.3688
Epoch [7/	10]	d_loss: 0.8704	g_loss: 3.5881
Epoch [7/	10]	d_loss: 0.9585	g_loss: 2.4453
Epoch [7/	10]	d_loss: 0.4768	g_loss: 1.6425
Epoch [8/	10]	d_loss: 2.9378	g_loss: 2.9804
Epoch [8/	10]	d_loss: 0.6097	g_loss: 1.6343
Epoch [8/	10]	d_loss: 0.4979	g_loss: 2.0315
Epoch [8/	10]	d_loss: 1.1367	g_loss: 0.8854
Epoch [8/	10]	d_loss: 0.6236	g_loss: 2.7084
Epoch [8/	10]	d_loss: 1.6523	g_loss: 1.7214
Epoch [8/	10]	d_loss: 0.4980	g_loss: 2.2070
Epoch [8/	10]	d_loss: 0.3637	g_loss: 1.5246
Epoch [8/	10]	d_loss: 1.1293	g_loss: 1.3270
Epoch [8/	10]	d_loss: 0.3432	g_loss: 2.8539
Epoch [8/	10]	d_loss: 0.4973	g_loss: 2.1048

Epoch [8/	10]	d_loss: 0.5901	g_loss: 1.6526
Epoch [8/	10]	d_loss: 1.3476	g_loss: 0.6706
Epoch [8/	10]	d_loss: 0.5845	g_loss: 2.2904
Epoch [8/	10]	d_loss: 0.3091	g_loss: 1.5830
Epoch [8/	10]	d_loss: 0.9885	g_loss: 1.6297
Epoch [8/	10]	d_loss: 0.5983	g_loss: 2.2942
Epoch [8/	10]	d_loss: 0.5554	g_loss: 1.3681
Epoch [8/	10]	d_loss: 1.0854	g_loss: 2.4241
Epoch [8/	10]	d_loss: 0.5710	g_loss: 2.3656
Epoch [8/	10]	d_loss: 0.4387	g_loss: 2.7304
Epoch [8/	10]	d_loss: 1.2052	g_loss: 1.8789
Epoch [8/	10]	d_loss: 1.2074	g_loss: 1.0615
Epoch [8/	10]	d_loss: 0.6868	g_loss: 1.5824
Epoch [8/	10]	d_loss: 0.4926	g_loss: 3.4491
Epoch [8/	10]	d_loss: 0.4231	g_loss: 1.5217
Epoch [8/	10]	d_loss: 1.0428	g_loss: 2.1677
Epoch [8/	10]	d_loss: 0.2972	g_loss: 1.2946
Epoch [8/	10]	d_loss: 0.8041	g_loss: 3.1981
Epoch [8/	10]	d_loss: 0.8686	g_loss: 1.7269
Epoch [8/	10]	d_loss: 0.5085	g_loss: 2.6916
Epoch [8/	10]	d_loss: 0.3462	g_loss: 2.3134
Epoch [8/	10]	d_loss: 1.7360	g_loss: 2.9243
Epoch [8/	10]	d_loss: 0.9660	g_loss: 1.7745
Epoch [8/	10]	d_loss: 0.7703	g_loss: 2.1716
Epoch [8/	10]	d_loss: 1.0452	g_loss: 3.7102
Epoch [8/	10]	d_loss: 1.0933	g_loss: 3.0051
Epoch [8/	10]	d_loss: 0.7725	g_loss: 2.0359
Epoch [8/	10]	d_loss: 0.6906	g_loss: 3.4893
Epoch [8/	10]	d_loss: 0.8943	g_loss: 1.7152
Epoch [8/	10]	d_loss: 1.0338	g_loss: 1.9187
Epoch [8/	10]	d_loss: 0.7761	g_loss: 1.3549
Epoch [8/	10]	d_loss: 1.1011	g_loss: 2.1753
Epoch [8/	10]	d_loss: 0.8745	g_loss: 2.4948
Epoch [8/	10]	d_loss: 0.7267	g_loss: 3.8147
Epoch [8/	10]	d_loss: 0.9170	g_loss: 1.9722
Epoch [8/	10]	d_loss: 0.3825	g_loss: 2.7486
Epoch [8/	10]	d_loss: 0.4469	g_loss: 2.1458
Epoch [8/	10]	d_loss: 1.1951	g_loss: 1.5294
Epoch [8/	10]	d_loss: 2.3043	g_loss: 0.7101
Epoch [8/	10]	d_loss: 0.7455	g_loss: 1.4687
Epoch [8/	10]	d_loss: 0.2634	g_loss: 1.5691
Epoch [8/	10]	d_loss: 1.0769	g_loss: 1.0944
Epoch [8/	10]	d_loss: 0.8411	g_loss: 1.3633
Epoch [8/	10]	d_loss: 0.6130	g_loss: 1.8845
Epoch [8/	10]	d_loss: 0.5217	g_loss: 2.2191
Epoch [8/	10]	d_loss: 0.3655	g_loss: 3.1503
Epoch [8/	10]	d_loss: 1.2430	g_loss: 1.7690
Epoch [8/	10]	d_loss: 0.4233	g_loss: 1.2055

Epoch [8/	10]	d_loss: 0.4025	g_loss: 2.7103
Epoch [8/	10]	d_loss: 1.1004	g_loss: 0.8154
Epoch [8/	10]	d_loss: 0.6026	g_loss: 3.3108
Epoch [8/	10]	d_loss: 1.3533	g_loss: 1.8102
Epoch [8/	10]	d_loss: 0.7400	g_loss: 1.7952
Epoch [8/	10]	d_loss: 1.1139	g_loss: 1.8628
Epoch [8/	10]	d_loss: 1.5291	g_loss: 4.0243
Epoch [8/	10]	d_loss: 0.4095	g_loss: 1.2706
Epoch [8/	10]	d_loss: 0.6405	g_loss: 1.8724
Epoch [8/	10]	d_loss: 0.7140	g_loss: 1.4117
Epoch [8/	10]	d_loss: 0.7494	g_loss: 2.5444
Epoch [8/	10]	d_loss: 0.8427	g_loss: 1.3891
Epoch [8/	10]	d_loss: 0.9890	g_loss: 2.3182
Epoch [8/	10]	d_loss: 0.7655	g_loss: 1.5913
Epoch [8/	10]	d_loss: 1.2147	g_loss: 2.3298
Epoch [8/	10]	d_loss: 0.5738	g_loss: 2.9920
Epoch [8/	10]	d_loss: 0.9584	g_loss: 2.6382
Epoch [8/	10]	d_loss: 0.5580	g_loss: 1.0629
Epoch [8/	10]	d_loss: 0.4603	g_loss: 2.4527
Epoch [8/	10]	d_loss: 0.8099	g_loss: 1.4474
Epoch [8/	10]	d_loss: 0.4595	g_loss: 1.1441
Epoch [8/	10]	d_loss: 0.9995	g_loss: 1.4232
Epoch [8/	10]	d_loss: 1.8931	g_loss: 2.1789
Epoch [8/	10]	d_loss: 0.9322	g_loss: 0.8737
Epoch [8/	10]	d_loss: 0.8810	g_loss: 1.6864
Epoch [8/	10]	d_loss: 0.4863	g_loss: 1.7784
Epoch [8/	10]	d_loss: 0.8927	g_loss: 1.1257
Epoch [8/	10]	d_loss: 0.4231	g_loss: 1.0993
Epoch [8/	10]	d_loss: 1.4181	g_loss: 2.1841
Epoch [8/	10]	d_loss: 0.2415	g_loss: 1.2264
Epoch [8/	10]	d_loss: 0.3946	g_loss: 2.1632
Epoch [8/	10]	d_loss: 0.6945	g_loss: 2.0483
Epoch [8/	10]	d_loss: 1.0866	g_loss: 1.5370
Epoch [8/	10]	d_loss: 1.2064	g_loss: 1.9515
Epoch [8/	10]	d_loss: 0.7395	g_loss: 0.7345
Epoch [8/	10]	d_loss: 1.0343	g_loss: 0.5984
Epoch [8/	10]	d_loss: 1.0966	g_loss: 2.9855
Epoch [8/	10]	d_loss: 0.8260	g_loss: 2.2644
Epoch [8/	10]	d_loss: 1.0635	g_loss: 1.6769
Epoch [8/	10]	d_loss: 1.3239	g_loss: 2.5696
Epoch [8/	10]	d_loss: 1.0901	g_loss: 1.4004
Epoch [9/	10]	d_loss: 0.9321	g_loss: 3.1480
Epoch [9/	10]	d_loss: 1.1239	g_loss: 2.5243
Epoch [9/	10]	d_loss: 0.9767	g_loss: 2.8008
Epoch [9/	10]	d_loss: 1.4319	g_loss: 1.2321
Epoch [9/	10]	d_loss: 0.3834	g_loss: 2.3047
Epoch [9/	10]	d_loss: 0.5417	g_loss: 1.7258
Epoch [9/	10]	d_loss: 0.7926	g_loss: 1.8377

Epoch [9/	10]	d_loss: 0.4733	g_loss: 2.9957
Epoch [9/	10]	d_loss: 0.9174	g_loss: 2.3099
Epoch [9/	10]	d_loss: 1.2035	g_loss: 2.5183
Epoch [9/	10]	d_loss: 1.5566	g_loss: 0.7784
Epoch [9/	10]	d_loss: 0.8621	g_loss: 1.1806
Epoch [9/	10]	d_loss: 1.4247	g_loss: 1.7312
Epoch [9/	10]	d_loss: 1.9501	g_loss: 1.9274
Epoch [9/	10]	d_loss: 0.8708	g_loss: 1.5998
Epoch [9/	10]	d_loss: 0.6810	g_loss: 2.6343
Epoch [9/	10]	d_loss: 0.6387	g_loss: 1.6795
Epoch [9/	10]	d_loss: 0.5452	g_loss: 1.4072
Epoch [9/	10]	d_loss: 0.1708	g_loss: 2.2024
Epoch [9/	10]	d_loss: 0.2877	g_loss: 2.0244
Epoch [9/	10]	d_loss: 0.4922	g_loss: 3.0152
Epoch [9/	10]	d_loss: 0.9586	g_loss: 1.0167
Epoch [9/	10]	d_loss: 1.6191	g_loss: 2.0786
Epoch [9/	10]	d_loss: 1.7914	g_loss: 2.9861
Epoch [9/	10]	d_loss: 0.5655	g_loss: 1.3467
Epoch [9/	10]	d_loss: 0.4552	g_loss: 3.0542
Epoch [9/	10]	d_loss: 1.0322	g_loss: 2.0347
Epoch [9/	10]	d_loss: 1.1033	g_loss: 1.8657
Epoch [9/	10]	d_loss: 0.4539	g_loss: 2.7818
Epoch [9/	10]	d_loss: 0.7398	g_loss: 1.5730
Epoch [9/	10]	d_loss: 1.3243	g_loss: 0.6444
Epoch [9/	10]	d_loss: 0.5161	g_loss: 1.3848
Epoch [9/	10]	d_loss: 0.3724	g_loss: 1.9004
Epoch [9/	10]	d_loss: 0.5955	g_loss: 1.5537
Epoch [9/	10]	d_loss: 1.0551	g_loss: 1.1622
Epoch [9/	10]	d_loss: 0.5970	g_loss: 1.9078
Epoch [9/	10]	d_loss: 0.2359	g_loss: 1.6797
Epoch [9/	10]	d_loss: 0.8216	g_loss: 1.7419
Epoch [9/	10]	d_loss: 1.1218	g_loss: 1.4767
Epoch [9/	10]	d_loss: 0.5889	g_loss: 1.8578
Epoch [9/	10]	d_loss: 0.1825	g_loss: 1.9152
Epoch [9/	10]	d_loss: 0.6550	g_loss: 1.2600
Epoch [9/	10]	d_loss: 1.2630	g_loss: 2.0470
Epoch [9/	10]	d_loss: 0.6999	g_loss: 1.4144
Epoch [9/	10]	d_loss: 2.2633	g_loss: 3.4960
Epoch [9/	10]	d_loss: 1.1029	g_loss: 0.7504
Epoch [9/	10]	d_loss: 0.6944	g_loss: 1.8402
Epoch [9/	10]	d_loss: 0.5141	g_loss: 2.0686
Epoch [9/	10]	d_loss: 0.1364	g_loss: 2.7845
Epoch [9/	10]	d_loss: 0.9466	g_loss: 2.5263
Epoch [9/	10]	d_loss: 1.0108	g_loss: 2.2659
Epoch [9/	10]	d_loss: 0.7348	g_loss: 2.0750
Epoch [9/	10]	d_loss: 0.6608	g_loss: 1.5533
Epoch [9/	10]	d_loss: 0.7609	g_loss: 1.9102
Epoch [9/	10]	d_loss: 0.9414	g_loss: 2.5171

Epoch [9/	10]	d_loss: 0.3575	g_loss: 1.9324
Epoch [9/	10]	d_loss: 0.8971	g_loss: 1.8939
Epoch [9/	10]	d_loss: 0.6388	g_loss: 2.2678
Epoch [9/	10]	d_loss: 1.3157	g_loss: 1.3496
Epoch [9/	10]	d_loss: 1.4573	g_loss: 2.8529
Epoch [9/	10]	d_loss: 0.3875	g_loss: 2.4588
Epoch [9/	10]	d_loss: 0.2258	g_loss: 1.3081
Epoch [9/	10]	d_loss: 0.6827	g_loss: 0.5956
Epoch [9/	10]	d_loss: 1.1255	g_loss: 1.9232
Epoch [9/	10]	d_loss: 0.7694	g_loss: 2.6143
Epoch [9/	10]	d_loss: 0.3538	g_loss: 1.7059
Epoch [9/	10]	d_loss: 1.0517	g_loss: 2.6027
Epoch [9/	10]	d_loss: 0.6363	g_loss: 1.5649
Epoch [9/	10]	d_loss: 1.1753	g_loss: 2.1410
Epoch [9/	10]	d_loss: 1.2480	g_loss: 1.0059
Epoch [9/	10]	d_loss: 0.8798	g_loss: 1.7851
Epoch [9/	10]	d_loss: 0.5981	g_loss: 2.4322
Epoch [9/	10]	d_loss: 0.5923	g_loss: 1.9523
Epoch [9/	10]	d_loss: 0.4431	g_loss: 2.5481
Epoch [9/	10]	d_loss: 0.8771	g_loss: 2.0252
Epoch [9/	10]	d_loss: 1.3419	g_loss: 2.3829
Epoch [9/	10]	d_loss: 0.9360	g_loss: 2.7776
Epoch [9/	10]	d_loss: 1.4222	g_loss: 1.0133
Epoch [9/	10]	d_loss: 0.8483	g_loss: 1.1853
Epoch [9/	10]	d_loss: 1.7422	g_loss: 3.7323
Epoch [9/	10]	d_loss: 1.5545	g_loss: 1.6867
Epoch [9/	10]	d_loss: 0.7861	g_loss: 2.8806
Epoch [9/	10]	d_loss: 0.8485	g_loss: 2.3086
Epoch [9/	10]	d_loss: 0.4572	g_loss: 1.4642
Epoch [9/	10]	d_loss: 0.3658	g_loss: 2.7106
Epoch [9/	10]	d_loss: 1.2979	g_loss: 1.2219
Epoch [9/	10]	d_loss: 0.8354	g_loss: 2.3110
Epoch [9/	10]	d_loss: 0.3110	g_loss: 1.4825
Epoch [9/	10]	d_loss: 0.5451	g_loss: 1.2895
Epoch [9/	10]	d_loss: 0.3220	g_loss: 2.5254
Epoch [9/	10]	d_loss: 2.1999	g_loss: 0.9681
Epoch [9/	10]	d_loss: 0.3138	g_loss: 3.5914
Epoch [9/	10]	d_loss: 1.0146	g_loss: 0.4605
Epoch [9/	10]	d_loss: 0.8892	g_loss: 1.2834
Epoch [9/	10]	d_loss: 0.8127	g_loss: 2.4615
Epoch [9/	10]	d_loss: 1.4326	g_loss: 1.1746
Epoch [9/	10]	d_loss: 0.5522	g_loss: 1.9938
Epoch [9/	10]	d_loss: 0.6867	g_loss: 2.7799
Epoch [9/	10]	d_loss: 1.5875	g_loss: 0.7334
Epoch [9/	10]	d_loss: 0.5499	g_loss: 1.4200
Epoch [10/	10]	d_loss: 2.8665	g_loss: 1.4005
Epoch [10/	10]	d_loss: 0.2722	g_loss: 1.4458
Epoch [10/	10]	d_loss: 0.8834	g_loss: 0.9132

Epoch [10/	10]	d_loss: 0.2268	g_loss: 2.5759
Epoch [10/	10]	d_loss: 1.2287	g_loss: 3.0111
Epoch [10/	10]	d_loss: 0.9425	g_loss: 2.0335
Epoch [10/	10]	d_loss: 0.8316	g_loss: 1.3084
Epoch [10/	10]	d_loss: 0.5183	g_loss: 1.6841
Epoch [10/	10]	d_loss: 0.6788	g_loss: 1.2244
Epoch [10/	10]	d_loss: 0.5956	g_loss: 2.6149
Epoch [10/	10]	d_loss: 0.9978	g_loss: 0.7222
Epoch [10/	10]	d_loss: 0.9038	g_loss: 2.6062
Epoch [10/	10]	d_loss: 0.3941	g_loss: 1.4206
Epoch [10/	10]	d_loss: 0.5781	g_loss: 2.4631
Epoch [10/	10]	d_loss: 0.7909	g_loss: 2.0529
Epoch [10/	10]	d_loss: 0.6050	g_loss: 1.3431
Epoch [10/	10]	d_loss: 0.8335	g_loss: 1.7802
Epoch [10/	10]	d_loss: 1.3020	g_loss: 1.0596
Epoch [10/	10]	d_loss: 0.9748	g_loss: 2.1436
Epoch [10/	10]	d_loss: 0.3386	g_loss: 1.8713
Epoch [10/	10]	d_loss: 1.4429	g_loss: 1.0957
Epoch [10/	10]	d_loss: 0.7899	g_loss: 2.1241
Epoch [10/	10]	d_loss: 0.4298	g_loss: 2.6489
Epoch [10/	10]	d_loss: 0.4039	g_loss: 1.1619
Epoch [10/	10]	d_loss: 2.0091	g_loss: 2.3962
Epoch [10/	10]	d_loss: 1.1100	g_loss: 1.8406
Epoch [10/	10]	d_loss: 0.4590	g_loss: 1.3664
Epoch [10/	10]	d_loss: 0.2132	g_loss: 1.0531
Epoch [10/	10]	d_loss: 1.2777	g_loss: 1.9357
Epoch [10/	10]	d_loss: 0.8609	g_loss: 1.8953
Epoch [10/	10]	d_loss: 0.6688	g_loss: 1.0325
Epoch [10/	10]	d_loss: 1.1353	g_loss: 1.8040
Epoch [10/	10]	d_loss: 0.2493	g_loss: 3.0940
Epoch [10/	10]	d_loss: 0.6083	g_loss: 1.8781
Epoch [10/	10]	d_loss: 0.7405	g_loss: 1.7332
Epoch [10/	10]	d_loss: 0.7258	g_loss: 1.9775
Epoch [10/	10]	d_loss: 0.2663	g_loss: 1.9508
Epoch [10/	10]	d_loss: 2.8762	g_loss: 1.4337
Epoch [10/	10]	d_loss: 0.4392	g_loss: 0.8164
Epoch [10/	10]	d_loss: 1.8846	g_loss: 1.8776
Epoch [10/	10]	d_loss: 0.6628	g_loss: 0.8596
Epoch [10/	10]	d_loss: 0.5123	g_loss: 1.0918
Epoch [10/	10]	d_loss: 0.4224	g_loss: 2.1514
Epoch [10/	10]	d_loss: 0.6825	g_loss: 0.9565
Epoch [10/	10]	d_loss: 1.9469	g_loss: 1.2477
Epoch [10/	10]	d_loss: 0.8199	g_loss: 3.2338
Epoch [10/	10]	d_loss: 1.0098	g_loss: 1.3360
Epoch [10/	10]	d_loss: 0.2010	g_loss: 2.5307
Epoch [10/	10]	d_loss: 0.8502	g_loss: 2.8041
Epoch [10/	10]	d_loss: 0.5666	g_loss: 2.4284
Epoch [10/	10]	d_loss: 0.8848	g_loss: 1.2131

Epoch [10/	10]	d_loss: 0.5240	g_loss: 2.0538
Epoch [10/	10]	d_loss: 0.6282	g_loss: 2.7748
Epoch [10/	10]	d_loss: 1.1031	g_loss: 0.5856
Epoch [10/	10]	d_loss: 0.7199	g_loss: 2.4936
Epoch [10/	10]	d_loss: 1.3112	g_loss: 2.5385
Epoch [10/	10]	d_loss: 0.7069	g_loss: 2.3468
Epoch [10/	10]	d_loss: 0.1247	g_loss: 1.1054
Epoch [10/	10]	d_loss: 0.5445	g_loss: 2.8792
Epoch [10/	10]	d_loss: 0.2235	g_loss: 1.0629
Epoch [10/	10]	d_loss: 1.4685	g_loss: 2.6151
Epoch [10/	10]	d_loss: 0.9871	g_loss: 1.1990
Epoch [10/	10]	d_loss: 0.5267	g_loss: 1.2767
Epoch [10/	10]	d_loss: 0.5458	g_loss: 2.7297
Epoch [10/	10]	d_loss: 1.1603	g_loss: 2.0369
Epoch [10/	10]	d_loss: 0.9981	g_loss: 1.2787
Epoch [10/	10]	d_loss: 0.3944	g_loss: 3.5747
Epoch [10/	10]	d_loss: 1.0510	g_loss: 3.8643
Epoch [10/	10]	d_loss: 0.8093	g_loss: 0.7995
Epoch [10/	10]	d_loss: 0.5618	g_loss: 1.3025
Epoch [10/	10]	d_loss: 0.7568	g_loss: 1.9658
Epoch [10/	10]	d_loss: 1.1235	g_loss: 1.5379
Epoch [10/	10]	d_loss: 0.7860	g_loss: 1.9740
Epoch [10/	10]	d_loss: 0.7712	g_loss: 3.9938
Epoch [10/	10]	d_loss: 0.6742	g_loss: 2.1079
Epoch [10/	10]	d_loss: 0.7714	g_loss: 3.6654
Epoch [10/	10]	d_loss: 0.9547	g_loss: 1.1724
Epoch [10/	10]	d_loss: 1.0860	g_loss: 1.6711
Epoch [10/	10]	d_loss: 1.1004	g_loss: 1.0528
Epoch [10/	10]	d_loss: 1.7372	g_loss: 1.1823
Epoch [10/	10]	d_loss: 0.4231	g_loss: 2.1299
Epoch [10/	10]	d_loss: 0.2075	g_loss: 2.2749
Epoch [10/	10]	d_loss: 1.2048	g_loss: 2.5277
Epoch [10/	10]	d_loss: 1.0253	g_loss: 0.8609
Epoch [10/	10]	d_loss: 0.5808	g_loss: 1.6271
Epoch [10/	10]	d_loss: 0.2108	g_loss: 4.5083
Epoch [10/	10]	d_loss: 0.7078	g_loss: 2.0553
Epoch [10/	10]	d_loss: 1.1755	g_loss: 1.6351
Epoch [10/	10]	d_loss: 0.1570	g_loss: 2.6834
Epoch [10/	10]	d_loss: 0.8121	g_loss: 1.6935
Epoch [10/	10]	d_loss: 1.5536	g_loss: 1.3697
Epoch [10/	10]	d_loss: 1.4764	g_loss: 2.8801
Epoch [10/	10]	d_loss: 1.0495	g_loss: 2.5536
Epoch [10/	10]	d_loss: 1.3047	g_loss: 0.4902
Epoch [10/	10]	d_loss: 0.9184	g_loss: 1.0453
Epoch [10/	10]	d_loss: 1.1294	g_loss: 0.8916
Epoch [10/	10]	d_loss: 0.8984	g_loss: 2.5977
Epoch [10/	10]	d_loss: 0.9602	g_loss: 1.7041
Epoch [10/	10]	d_loss: 0.7802	g_loss: 2.6553

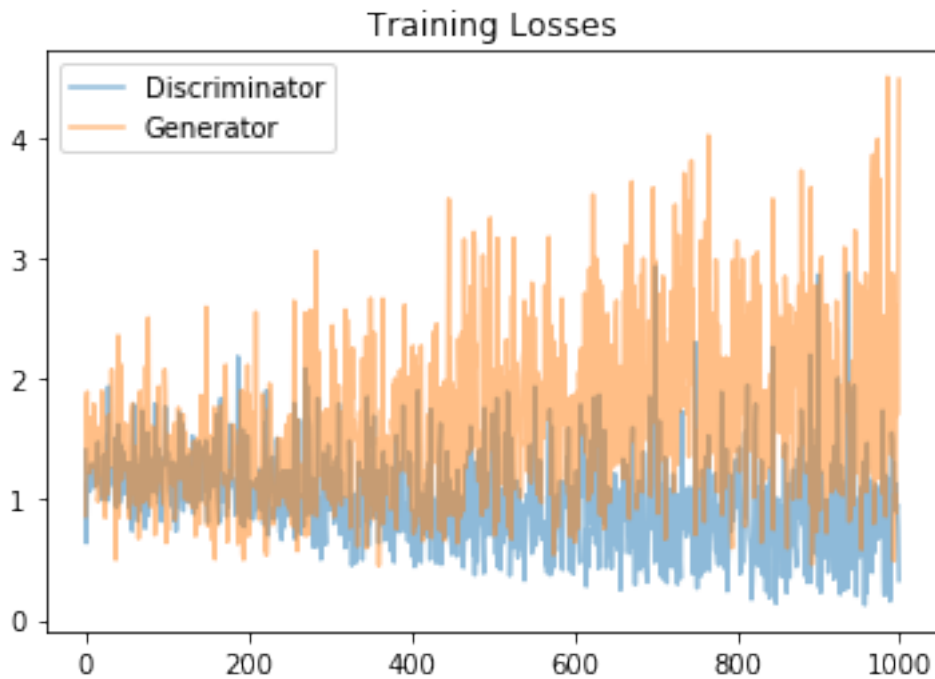
Epoch [10/ 10] | d_loss: 0.3297 | g_loss: 4.4885

2.8 Training loss

Plot the training losses for the generator and discriminator, recorded after each epoch.

```
In [19]: fig, ax = plt.subplots()
         losses = np.array(losses)
         plt.plot(losses.T[0], label='Discriminator', alpha=0.5)
         plt.plot(losses.T[1], label='Generator', alpha=0.5)
         plt.title("Training Losses")
         plt.legend()
```

Out[19]: <matplotlib.legend.Legend at 0x7f34e72916d8>



2.9 Generator samples from training

View samples of images from the generator, and answer a question about the strengths and weaknesses of your trained models.

```
In [20]: # helper function for viewing a list of passed in sample images
         def view_samples(epoch, samples):
             fig, axes = plt.subplots(figsize=(16,4), nrows=2, ncols=8, sharey=True, sharex=True)
             for ax, img in zip(axes.flatten(), samples[epoch]):
```

```

img = img.detach().cpu().numpy()
img = np.transpose(img, (1, 2, 0))
img = ((img + 1)*255 / (2)).astype(np.uint8)
ax.xaxis.set_visible(False)
ax.yaxis.set_visible(False)
im = ax.imshow(img.reshape((32,32,3)))

```

```

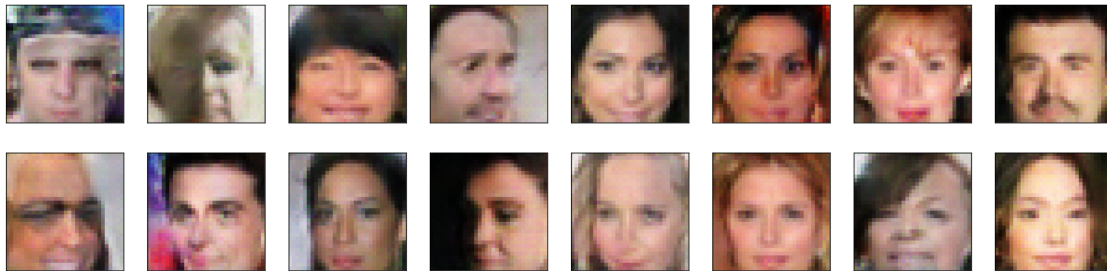
In [21]: # Load samples from generator, taken while training
with open('train_samples.pkl', 'rb') as f:
    samples = pickle.load(f)

```

```

In [22]: _ = view_samples(-1, samples)

```



2.9.1 Question: What do you notice about your generated samples and how might you improve this model?

When you answer this question, consider the following factors: * The dataset is biased; it is made of “celebrity” faces that are mostly white * Model size; larger models have the opportunity to learn more features in a data feature space * Optimization strategy; optimizers and number of epochs affect your final result

Answer: (Write your answer in this cell)

The GAN generated pictures of faces. I want to mention that they are under different angles and pictures are not damaged because of that. I might train for more than 10 epochs to further improve but there is a limit of epochs that depends of the spread between generator and discriminator batch size when no further improvement occurs. Model is deep as generator and as well as discriminator and they work at maximum capacity considering in the input size and output size.

Definitely, more variety of faces might help to train neural network better and generate a new type of faces.

Model size matters we have to ensure that our models recognize and generate faces correctly. Deep models allow to catch some more characteristics of the faces.

I used suggested beta1 0.3 and it generated more types of faces than beta1 0.5 which was suggested by the paper. Adam is the best choice for GAN's as well as other architectures. Number of epochs is a critical component of GAN's. Especially spread between batch size of a generator and a discriminator.

2.9.2 Submitting This Project

When submitting this project, make sure to run all the cells before saving the notebook. Save the notebook file as “dlnd_face_generation.ipynb” and save it as a HTML file under “File” -> “Download as”. Include the “problem_unittests.py” files in your submission.