

dlnd_face_generation0

December 4, 2021

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

```
In [32]: 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 [33]: # necessary imports
```

```
import torch
from torchvision import datasets
from torchvision import transforms
```

```
In [34]: 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
```

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

```

dataset = datasets.ImageFolder(data_dir, transform)

dataloader = torch.utils.data.DataLoader(dataset=dataset, batch_size=batch_size, sh

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 [35]: # 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.

```

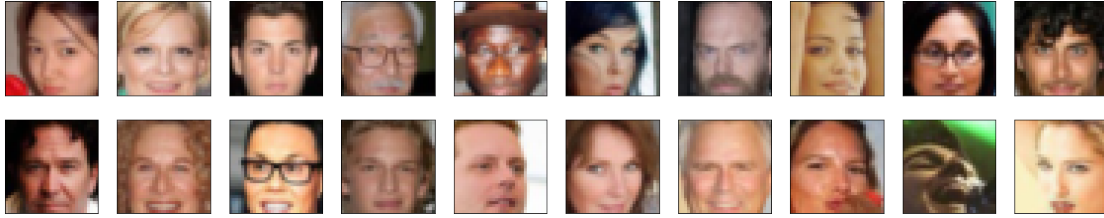
In [36]: # helper display function
def imshow(img):
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))

"""
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 [37]: # 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

    min , max = feature_range

    x = x * (max-min) + min

    return x
```

```
In [38]: """
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(-1.)
Max:  tensor(0.9373)
```

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

2.2 Helper Function

```
In [40]: # helper conv function
def conv(in_channels, out_channels, kernel_size, stride=2, padding=1, batch_norm=True):
    """Creates a convolutional layer, with optional batch normalization.
    """
    layers = []
    conv_layer = nn.Conv2d(in_channels=in_channels, out_channels=out_channels,
                           kernel_size=kernel_size, stride=stride, padding=padding, bias=True)
    layers.append(conv_layer)

    if batch_norm:
        layers.append(nn.BatchNorm2d(out_channels))
    return nn.Sequential(*layers)

# helper deconv function
def deconv(in_channels, out_channels, kernel_size, stride=2, padding=1, batch_norm=True):
    """Creates a transpose convolutional layer, with optional batch normalization.
    """
    layers = []
    # append transpose conv layer
    layers.append(nn.ConvTranspose2d(in_channels, out_channels, kernel_size, stride, padding=padding))
    # optional batch norm layer
    if batch_norm:
        layers.append(nn.BatchNorm2d(out_channels))
    return nn.Sequential(*layers)

In [41]: 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, stride=2, padding=1, bias=False, kernel_size=3)
        self.batch_norm1 = nn.BatchNorm2d(conv_dim)

        self.conv2 = nn.Conv2d(conv_dim, conv_dim*2, stride=2, padding=1, bias=False, kernel_size=3)
        self.batch_norm2 = nn.BatchNorm2d(conv_dim*2)

        self.conv3 = nn.Conv2d(conv_dim*2, conv_dim*4, stride=2, padding=1, bias=False, kernel_size=3)
        self.batch_norm3 = nn.BatchNorm2d(conv_dim*4)

        self.conv4 = nn.Conv2d(conv_dim*4, conv_dim*8, stride=2, padding=1, bias=False, kernel_size=3)
        self.batch_norm4 = nn.BatchNorm2d(conv_dim*8)

        self.conv5 = nn.Conv2d(conv_dim*8, conv_dim*16, stride=2, padding=1, bias=False, kernel_size=3)
        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)

    x = x.view(-1, self.conv_dim*4*4)

    # 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

2.3 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 [42]: `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
    """
    super(Generator, self).__init__()

    # complete init function

    self.conv_dim = conv_dim

    self.t_conv1 = nn.ConvTranspose2d(conv_dim, conv_dim*8, stride=2, padding=1, bias=False)
    self.batch_norm1 = nn.BatchNorm2d(conv_dim*8)

    self.t_conv2 = nn.ConvTranspose2d(conv_dim*8, conv_dim*4, stride=2, padding=1, bias=False)
    self.batch_norm2 = nn.BatchNorm2d(conv_dim*4)

    self.t_conv3 = nn.ConvTranspose2d(conv_dim*4, conv_dim*2, stride=2, padding=1, bias=False)
    self.batch_norm3 = nn.BatchNorm2d(conv_dim*2)

    self.t_conv4 = nn.ConvTranspose2d(conv_dim*2, 3, stride=2, padding=1, bias=False)

    self.fc = nn.Linear(z_size, conv_dim*4)

```

```

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)

    # output layer
    x = F.tanh(x)

    return x

    """
    DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
    """
    tests.test_generator(Generator)

```

Tests Passed

2.4 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 [43]: 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 (classname.find('Conv') != -1 or classname.find('Linear') != -1) and hasattr(m,
            nn.init.normal_(m.weight.data, 0.0, 0.02)
```

2.5 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 [44]: """
        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 [45]: # 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)

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=False)
    (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=False)
    (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=False)
    (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)
)

```

2.5.1 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 [46]: """
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!

2.6 Discriminator and Generator Losses

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

2.6.1 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.

2.6.2 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 [47]: import random
         def real_loss(D_out, smooth=False):

             batch_size = D_out.size(0)

             labels = torch.ones(batch_size)*0.9

             if train_on_gpu:
                 labels = labels.cuda()

             criterion = nn.BCELoss()

             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()

loss = criterion(D_out.squeeze(), labels)

return loss

```

2.7 Optimizers

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

```

In [48]: import torch.optim as optim

d_optimizer = optim.Adam(D.parameters(), lr=0.0005, betas=(0.1, 0.999))
g_optimizer = optim.Adam(G.parameters(), lr=0.0005, betas=(0.1, 0.999))

```

2.8 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 [49]: 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)

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 [50]: # 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: 1.3672 | g_loss: 1.0886
Epoch [ 1/ 10] | d_loss: 1.3421 | g_loss: 0.8818
Epoch [ 1/ 10] | d_loss: 1.3073 | g_loss: 1.1071
Epoch [ 1/ 10] | d_loss: 1.2262 | g_loss: 1.0877
Epoch [ 1/ 10] | d_loss: 1.3660 | g_loss: 0.9414
Epoch [ 1/ 10] | d_loss: 1.2818 | g_loss: 1.0140
Epoch [ 1/ 10] | d_loss: 1.4973 | g_loss: 1.3645
Epoch [ 1/ 10] | d_loss: 1.2064 | g_loss: 1.1135
Epoch [ 1/ 10] | d_loss: 1.3753 | g_loss: 1.2552
Epoch [ 1/ 10] | d_loss: 1.3895 | g_loss: 0.9882
Epoch [ 1/ 10] | d_loss: 1.3851 | g_loss: 1.1609
Epoch [ 1/ 10] | d_loss: 1.2684 | g_loss: 0.6966
Epoch [ 1/ 10] | d_loss: 1.3501 | g_loss: 1.1292
Epoch [ 1/ 10] | d_loss: 1.4714 | g_loss: 0.8745
Epoch [ 1/ 10] | d_loss: 1.3516 | g_loss: 0.8411
Epoch [ 1/ 10] | d_loss: 1.2655 | g_loss: 1.2381
Epoch [ 1/ 10] | d_loss: 1.2893 | g_loss: 1.3190
Epoch [ 1/ 10] | d_loss: 1.3110 | g_loss: 1.0625
Epoch [ 1/ 10] | d_loss: 1.3922 | g_loss: 0.9080
Epoch [ 1/ 10] | d_loss: 1.3250 | g_loss: 1.1447
Epoch [ 1/ 10] | d_loss: 1.4751 | g_loss: 1.4620

```

Epoch [1/	10]	d_loss: 1.1810	g_loss: 1.0830
Epoch [1/	10]	d_loss: 1.4004	g_loss: 1.0486
Epoch [1/	10]	d_loss: 1.5283	g_loss: 0.7456
Epoch [1/	10]	d_loss: 1.2398	g_loss: 0.9128
Epoch [1/	10]	d_loss: 1.2065	g_loss: 1.1173
Epoch [1/	10]	d_loss: 1.1402	g_loss: 1.1840
Epoch [1/	10]	d_loss: 1.2978	g_loss: 1.0721
Epoch [1/	10]	d_loss: 1.2298	g_loss: 1.1749
Epoch [1/	10]	d_loss: 1.2470	g_loss: 1.1691
Epoch [1/	10]	d_loss: 1.4999	g_loss: 1.1199
Epoch [1/	10]	d_loss: 1.3228	g_loss: 0.8521
Epoch [1/	10]	d_loss: 1.3046	g_loss: 0.9676
Epoch [1/	10]	d_loss: 1.2502	g_loss: 1.2177
Epoch [1/	10]	d_loss: 1.3350	g_loss: 0.9156
Epoch [1/	10]	d_loss: 1.2001	g_loss: 0.8926
Epoch [1/	10]	d_loss: 1.2576	g_loss: 0.8891
Epoch [1/	10]	d_loss: 1.3140	g_loss: 1.7108
Epoch [1/	10]	d_loss: 1.4057	g_loss: 1.1084
Epoch [1/	10]	d_loss: 1.3621	g_loss: 0.9693
Epoch [1/	10]	d_loss: 1.4201	g_loss: 1.1529
Epoch [1/	10]	d_loss: 1.2713	g_loss: 1.7139
Epoch [1/	10]	d_loss: 1.2314	g_loss: 1.2424
Epoch [1/	10]	d_loss: 1.3641	g_loss: 1.3670
Epoch [1/	10]	d_loss: 1.3636	g_loss: 0.8177
Epoch [1/	10]	d_loss: 1.3175	g_loss: 0.9847
Epoch [1/	10]	d_loss: 1.3964	g_loss: 1.4086
Epoch [1/	10]	d_loss: 1.1211	g_loss: 1.1305
Epoch [1/	10]	d_loss: 1.1421	g_loss: 1.0860
Epoch [1/	10]	d_loss: 1.0557	g_loss: 1.0966
Epoch [1/	10]	d_loss: 1.1072	g_loss: 1.0076
Epoch [1/	10]	d_loss: 1.1771	g_loss: 1.2768
Epoch [1/	10]	d_loss: 1.3369	g_loss: 0.8655
Epoch [1/	10]	d_loss: 1.3186	g_loss: 1.0367
Epoch [1/	10]	d_loss: 1.2296	g_loss: 0.8887
Epoch [1/	10]	d_loss: 1.3247	g_loss: 1.0291
Epoch [1/	10]	d_loss: 1.1041	g_loss: 1.2561
Epoch [1/	10]	d_loss: 1.3483	g_loss: 1.0542
Epoch [1/	10]	d_loss: 1.4174	g_loss: 1.1418
Epoch [1/	10]	d_loss: 1.3411	g_loss: 0.8333
Epoch [1/	10]	d_loss: 1.2455	g_loss: 1.7522
Epoch [1/	10]	d_loss: 1.1916	g_loss: 1.6224
Epoch [1/	10]	d_loss: 1.3306	g_loss: 0.9382
Epoch [1/	10]	d_loss: 1.1401	g_loss: 1.3180
Epoch [1/	10]	d_loss: 1.2320	g_loss: 0.8547
Epoch [1/	10]	d_loss: 1.0980	g_loss: 1.4262
Epoch [1/	10]	d_loss: 1.2479	g_loss: 1.5171
Epoch [1/	10]	d_loss: 1.3520	g_loss: 1.3944
Epoch [1/	10]	d_loss: 1.0850	g_loss: 1.3813

Epoch [1/	10]	d_loss: 0.9317	g_loss: 1.1432
Epoch [1/	10]	d_loss: 1.2338	g_loss: 1.3583
Epoch [1/	10]	d_loss: 1.3027	g_loss: 1.6450
Epoch [1/	10]	d_loss: 1.1465	g_loss: 1.0541
Epoch [1/	10]	d_loss: 1.3121	g_loss: 1.2595
Epoch [1/	10]	d_loss: 1.2587	g_loss: 1.3023
Epoch [1/	10]	d_loss: 1.6852	g_loss: 0.9090
Epoch [1/	10]	d_loss: 1.1302	g_loss: 1.1788
Epoch [1/	10]	d_loss: 1.2020	g_loss: 0.8436
Epoch [1/	10]	d_loss: 1.2754	g_loss: 0.7723
Epoch [1/	10]	d_loss: 1.1880	g_loss: 0.5999
Epoch [1/	10]	d_loss: 1.1528	g_loss: 1.1876
Epoch [1/	10]	d_loss: 1.2460	g_loss: 1.1575
Epoch [1/	10]	d_loss: 1.3811	g_loss: 1.0860
Epoch [1/	10]	d_loss: 1.1452	g_loss: 1.1577
Epoch [1/	10]	d_loss: 1.2473	g_loss: 1.1288
Epoch [1/	10]	d_loss: 1.2628	g_loss: 0.9991
Epoch [1/	10]	d_loss: 1.2340	g_loss: 1.6049
Epoch [1/	10]	d_loss: 1.4918	g_loss: 0.7308
Epoch [1/	10]	d_loss: 1.3216	g_loss: 1.3419
Epoch [1/	10]	d_loss: 1.3529	g_loss: 1.3533
Epoch [2/	10]	d_loss: 1.1411	g_loss: 1.5131
Epoch [2/	10]	d_loss: 1.3307	g_loss: 1.1558
Epoch [2/	10]	d_loss: 1.1801	g_loss: 1.3273
Epoch [2/	10]	d_loss: 1.4406	g_loss: 0.8971
Epoch [2/	10]	d_loss: 1.2953	g_loss: 0.9075
Epoch [2/	10]	d_loss: 1.1273	g_loss: 1.0304
Epoch [2/	10]	d_loss: 1.4566	g_loss: 0.8378
Epoch [2/	10]	d_loss: 1.2443	g_loss: 1.1187
Epoch [2/	10]	d_loss: 1.3641	g_loss: 0.7740
Epoch [2/	10]	d_loss: 1.3697	g_loss: 1.6206
Epoch [2/	10]	d_loss: 1.2009	g_loss: 1.2932
Epoch [2/	10]	d_loss: 1.2054	g_loss: 0.9936
Epoch [2/	10]	d_loss: 1.0558	g_loss: 2.0262
Epoch [2/	10]	d_loss: 1.0004	g_loss: 1.1284
Epoch [2/	10]	d_loss: 1.1736	g_loss: 1.8629
Epoch [2/	10]	d_loss: 1.1254	g_loss: 1.1790
Epoch [2/	10]	d_loss: 1.0286	g_loss: 1.2118
Epoch [2/	10]	d_loss: 1.4907	g_loss: 0.9720
Epoch [2/	10]	d_loss: 1.1612	g_loss: 1.0259
Epoch [2/	10]	d_loss: 1.1232	g_loss: 1.0101
Epoch [2/	10]	d_loss: 1.1769	g_loss: 0.8116
Epoch [2/	10]	d_loss: 1.0048	g_loss: 1.2042
Epoch [2/	10]	d_loss: 1.3592	g_loss: 1.1877
Epoch [2/	10]	d_loss: 1.2660	g_loss: 1.1102
Epoch [2/	10]	d_loss: 0.9993	g_loss: 1.7251
Epoch [2/	10]	d_loss: 1.2107	g_loss: 1.2333
Epoch [2/	10]	d_loss: 1.1531	g_loss: 0.9990

Epoch [2/	10]	d_loss: 0.9075	g_loss: 1.2403
Epoch [2/	10]	d_loss: 1.2554	g_loss: 1.1904
Epoch [2/	10]	d_loss: 1.0282	g_loss: 1.0729
Epoch [2/	10]	d_loss: 1.1336	g_loss: 1.0575
Epoch [2/	10]	d_loss: 0.9535	g_loss: 1.3588
Epoch [2/	10]	d_loss: 1.1825	g_loss: 1.5823
Epoch [2/	10]	d_loss: 1.5623	g_loss: 0.9093
Epoch [2/	10]	d_loss: 1.1201	g_loss: 0.9919
Epoch [2/	10]	d_loss: 1.2705	g_loss: 2.1539
Epoch [2/	10]	d_loss: 1.1784	g_loss: 1.3464
Epoch [2/	10]	d_loss: 1.1960	g_loss: 0.8887
Epoch [2/	10]	d_loss: 1.1347	g_loss: 1.2501
Epoch [2/	10]	d_loss: 1.3046	g_loss: 1.8206
Epoch [2/	10]	d_loss: 1.0166	g_loss: 1.6089
Epoch [2/	10]	d_loss: 1.4041	g_loss: 1.7583
Epoch [2/	10]	d_loss: 1.2788	g_loss: 1.1545
Epoch [2/	10]	d_loss: 1.1798	g_loss: 1.6525
Epoch [2/	10]	d_loss: 1.1333	g_loss: 1.4349
Epoch [2/	10]	d_loss: 1.2359	g_loss: 0.7339
Epoch [2/	10]	d_loss: 1.2618	g_loss: 1.7236
Epoch [2/	10]	d_loss: 1.1358	g_loss: 1.2800
Epoch [2/	10]	d_loss: 1.1729	g_loss: 0.9888
Epoch [2/	10]	d_loss: 1.2793	g_loss: 1.2015
Epoch [2/	10]	d_loss: 1.0723	g_loss: 1.2559
Epoch [2/	10]	d_loss: 1.1544	g_loss: 0.9833
Epoch [2/	10]	d_loss: 1.1143	g_loss: 0.7342
Epoch [2/	10]	d_loss: 1.4485	g_loss: 2.8123
Epoch [2/	10]	d_loss: 1.3108	g_loss: 1.5610
Epoch [2/	10]	d_loss: 1.3001	g_loss: 1.4948
Epoch [2/	10]	d_loss: 1.0258	g_loss: 1.0540
Epoch [2/	10]	d_loss: 1.0193	g_loss: 1.1398
Epoch [2/	10]	d_loss: 1.4206	g_loss: 0.7746
Epoch [2/	10]	d_loss: 1.0473	g_loss: 1.1509
Epoch [2/	10]	d_loss: 1.2610	g_loss: 1.3287
Epoch [2/	10]	d_loss: 1.3150	g_loss: 1.3756
Epoch [2/	10]	d_loss: 0.9603	g_loss: 1.1721
Epoch [2/	10]	d_loss: 1.0668	g_loss: 1.8175
Epoch [2/	10]	d_loss: 1.1023	g_loss: 0.8590
Epoch [2/	10]	d_loss: 1.2278	g_loss: 1.0417
Epoch [2/	10]	d_loss: 0.9903	g_loss: 1.7132
Epoch [2/	10]	d_loss: 0.9511	g_loss: 1.2121
Epoch [2/	10]	d_loss: 1.2575	g_loss: 1.4350
Epoch [2/	10]	d_loss: 1.2326	g_loss: 0.9766
Epoch [2/	10]	d_loss: 1.2038	g_loss: 1.2484
Epoch [2/	10]	d_loss: 1.6012	g_loss: 0.8423
Epoch [2/	10]	d_loss: 1.0029	g_loss: 1.3464
Epoch [2/	10]	d_loss: 1.1588	g_loss: 1.7149
Epoch [2/	10]	d_loss: 1.0459	g_loss: 1.3538

Epoch [2/	10]	d_loss: 1.0022	g_loss: 1.6057
Epoch [2/	10]	d_loss: 1.1957	g_loss: 1.3472
Epoch [2/	10]	d_loss: 0.9552	g_loss: 1.9001
Epoch [2/	10]	d_loss: 0.8936	g_loss: 1.5590
Epoch [2/	10]	d_loss: 1.0533	g_loss: 1.0887
Epoch [2/	10]	d_loss: 1.2081	g_loss: 0.8361
Epoch [2/	10]	d_loss: 1.2661	g_loss: 1.8617
Epoch [2/	10]	d_loss: 1.2017	g_loss: 0.9899
Epoch [2/	10]	d_loss: 0.9712	g_loss: 1.2098
Epoch [2/	10]	d_loss: 1.1134	g_loss: 0.9540
Epoch [2/	10]	d_loss: 1.1393	g_loss: 1.0611
Epoch [2/	10]	d_loss: 0.8355	g_loss: 1.1846
Epoch [2/	10]	d_loss: 1.3635	g_loss: 0.8841
Epoch [2/	10]	d_loss: 1.0337	g_loss: 1.0671
Epoch [2/	10]	d_loss: 1.4958	g_loss: 0.9028
Epoch [3/	10]	d_loss: 0.9749	g_loss: 1.4954
Epoch [3/	10]	d_loss: 0.8502	g_loss: 1.1088
Epoch [3/	10]	d_loss: 0.9796	g_loss: 1.8277
Epoch [3/	10]	d_loss: 1.0112	g_loss: 1.6665
Epoch [3/	10]	d_loss: 1.5597	g_loss: 2.4891
Epoch [3/	10]	d_loss: 1.1545	g_loss: 1.6196
Epoch [3/	10]	d_loss: 1.3250	g_loss: 2.2937
Epoch [3/	10]	d_loss: 1.3831	g_loss: 1.4257
Epoch [3/	10]	d_loss: 1.1790	g_loss: 1.3857
Epoch [3/	10]	d_loss: 1.1193	g_loss: 1.0749
Epoch [3/	10]	d_loss: 1.0201	g_loss: 0.9541
Epoch [3/	10]	d_loss: 1.3519	g_loss: 1.1638
Epoch [3/	10]	d_loss: 0.9396	g_loss: 1.0898
Epoch [3/	10]	d_loss: 1.2277	g_loss: 0.8996
Epoch [3/	10]	d_loss: 0.9042	g_loss: 1.7941
Epoch [3/	10]	d_loss: 0.9506	g_loss: 1.2510
Epoch [3/	10]	d_loss: 1.2091	g_loss: 1.7356
Epoch [3/	10]	d_loss: 1.5946	g_loss: 1.0611
Epoch [3/	10]	d_loss: 1.0240	g_loss: 1.0768
Epoch [3/	10]	d_loss: 0.8342	g_loss: 1.8790
Epoch [3/	10]	d_loss: 1.1164	g_loss: 1.2486
Epoch [3/	10]	d_loss: 1.2151	g_loss: 1.0905
Epoch [3/	10]	d_loss: 1.1871	g_loss: 1.5997
Epoch [3/	10]	d_loss: 1.2114	g_loss: 1.3998
Epoch [3/	10]	d_loss: 1.1944	g_loss: 1.1262
Epoch [3/	10]	d_loss: 1.1230	g_loss: 0.9411
Epoch [3/	10]	d_loss: 1.2969	g_loss: 0.8282
Epoch [3/	10]	d_loss: 1.0586	g_loss: 2.1297
Epoch [3/	10]	d_loss: 0.8721	g_loss: 1.6437
Epoch [3/	10]	d_loss: 1.1644	g_loss: 0.9337
Epoch [3/	10]	d_loss: 1.1340	g_loss: 1.4382
Epoch [3/	10]	d_loss: 0.9278	g_loss: 1.3241
Epoch [3/	10]	d_loss: 0.9010	g_loss: 1.6117

Epoch [3/	10]	d_loss: 1.1474	g_loss: 1.5314
Epoch [3/	10]	d_loss: 1.0737	g_loss: 1.0175
Epoch [3/	10]	d_loss: 1.2960	g_loss: 1.1198
Epoch [3/	10]	d_loss: 1.2042	g_loss: 1.4942
Epoch [3/	10]	d_loss: 1.0855	g_loss: 1.7304
Epoch [3/	10]	d_loss: 1.2687	g_loss: 1.2702
Epoch [3/	10]	d_loss: 1.2324	g_loss: 1.0542
Epoch [3/	10]	d_loss: 1.3124	g_loss: 1.7940
Epoch [3/	10]	d_loss: 0.9083	g_loss: 1.4828
Epoch [3/	10]	d_loss: 1.0250	g_loss: 1.7628
Epoch [3/	10]	d_loss: 1.1446	g_loss: 1.0654
Epoch [3/	10]	d_loss: 1.0182	g_loss: 0.9536
Epoch [3/	10]	d_loss: 1.1230	g_loss: 1.0278
Epoch [3/	10]	d_loss: 1.0140	g_loss: 1.9132
Epoch [3/	10]	d_loss: 1.3588	g_loss: 0.6708
Epoch [3/	10]	d_loss: 1.1095	g_loss: 1.4425
Epoch [3/	10]	d_loss: 1.0737	g_loss: 1.3366
Epoch [3/	10]	d_loss: 1.0459	g_loss: 1.6088
Epoch [3/	10]	d_loss: 0.9479	g_loss: 2.0012
Epoch [3/	10]	d_loss: 1.4986	g_loss: 0.8846
Epoch [3/	10]	d_loss: 1.0554	g_loss: 1.3326
Epoch [3/	10]	d_loss: 0.9682	g_loss: 1.4190
Epoch [3/	10]	d_loss: 0.7255	g_loss: 2.5005
Epoch [3/	10]	d_loss: 1.0955	g_loss: 1.9457
Epoch [3/	10]	d_loss: 1.2296	g_loss: 1.9799
Epoch [3/	10]	d_loss: 0.8702	g_loss: 0.9167
Epoch [3/	10]	d_loss: 1.2017	g_loss: 1.5151
Epoch [3/	10]	d_loss: 0.8994	g_loss: 2.3413
Epoch [3/	10]	d_loss: 1.3342	g_loss: 1.4424
Epoch [3/	10]	d_loss: 1.3889	g_loss: 1.0654
Epoch [3/	10]	d_loss: 0.9939	g_loss: 1.9272
Epoch [3/	10]	d_loss: 0.9492	g_loss: 1.5764
Epoch [3/	10]	d_loss: 0.9554	g_loss: 1.8875
Epoch [3/	10]	d_loss: 1.5843	g_loss: 1.0497
Epoch [3/	10]	d_loss: 1.2108	g_loss: 1.1362
Epoch [3/	10]	d_loss: 1.3795	g_loss: 1.0430
Epoch [3/	10]	d_loss: 0.9584	g_loss: 1.5924
Epoch [3/	10]	d_loss: 1.0044	g_loss: 1.3433
Epoch [3/	10]	d_loss: 1.0313	g_loss: 1.6026
Epoch [3/	10]	d_loss: 0.8859	g_loss: 1.3749
Epoch [3/	10]	d_loss: 0.8756	g_loss: 1.1832
Epoch [3/	10]	d_loss: 1.2413	g_loss: 1.2658
Epoch [3/	10]	d_loss: 0.8954	g_loss: 1.3421
Epoch [3/	10]	d_loss: 1.1650	g_loss: 1.2642
Epoch [3/	10]	d_loss: 1.1828	g_loss: 1.1256
Epoch [3/	10]	d_loss: 1.1482	g_loss: 0.7817
Epoch [3/	10]	d_loss: 0.9402	g_loss: 1.5207
Epoch [3/	10]	d_loss: 1.0202	g_loss: 1.6878

Epoch [3/	10]	d_loss: 1.2564	g_loss: 1.9934
Epoch [3/	10]	d_loss: 0.9457	g_loss: 1.2762
Epoch [3/	10]	d_loss: 1.1041	g_loss: 0.7847
Epoch [3/	10]	d_loss: 1.0631	g_loss: 1.5912
Epoch [3/	10]	d_loss: 1.2338	g_loss: 2.7168
Epoch [3/	10]	d_loss: 0.9120	g_loss: 1.5773
Epoch [3/	10]	d_loss: 1.5467	g_loss: 1.5629
Epoch [3/	10]	d_loss: 1.1550	g_loss: 1.9785
Epoch [3/	10]	d_loss: 1.2438	g_loss: 1.5133
Epoch [4/	10]	d_loss: 1.4750	g_loss: 2.8702
Epoch [4/	10]	d_loss: 0.6072	g_loss: 1.4901
Epoch [4/	10]	d_loss: 1.0764	g_loss: 0.7908
Epoch [4/	10]	d_loss: 0.8356	g_loss: 1.4112
Epoch [4/	10]	d_loss: 1.6632	g_loss: 1.0487
Epoch [4/	10]	d_loss: 0.7687	g_loss: 1.0168
Epoch [4/	10]	d_loss: 0.8629	g_loss: 1.5379
Epoch [4/	10]	d_loss: 1.1319	g_loss: 1.1280
Epoch [4/	10]	d_loss: 1.0561	g_loss: 1.3680
Epoch [4/	10]	d_loss: 1.5976	g_loss: 2.3532
Epoch [4/	10]	d_loss: 0.8213	g_loss: 1.7691
Epoch [4/	10]	d_loss: 1.1104	g_loss: 1.3896
Epoch [4/	10]	d_loss: 1.0576	g_loss: 1.0102
Epoch [4/	10]	d_loss: 1.7827	g_loss: 2.7244
Epoch [4/	10]	d_loss: 1.1371	g_loss: 0.9083
Epoch [4/	10]	d_loss: 1.0835	g_loss: 1.6127
Epoch [4/	10]	d_loss: 0.8314	g_loss: 1.9983
Epoch [4/	10]	d_loss: 1.2960	g_loss: 1.7327
Epoch [4/	10]	d_loss: 0.8968	g_loss: 1.0884
Epoch [4/	10]	d_loss: 1.0863	g_loss: 2.3617
Epoch [4/	10]	d_loss: 1.4677	g_loss: 1.2057
Epoch [4/	10]	d_loss: 0.8588	g_loss: 1.1154
Epoch [4/	10]	d_loss: 0.9684	g_loss: 1.2404
Epoch [4/	10]	d_loss: 1.7143	g_loss: 2.8408
Epoch [4/	10]	d_loss: 1.4721	g_loss: 1.8689
Epoch [4/	10]	d_loss: 0.9581	g_loss: 1.9336
Epoch [4/	10]	d_loss: 1.4875	g_loss: 1.5862
Epoch [4/	10]	d_loss: 0.8420	g_loss: 1.0559
Epoch [4/	10]	d_loss: 0.9197	g_loss: 1.6165
Epoch [4/	10]	d_loss: 0.8185	g_loss: 1.2632
Epoch [4/	10]	d_loss: 1.3743	g_loss: 1.2937
Epoch [4/	10]	d_loss: 1.0642	g_loss: 0.7015
Epoch [4/	10]	d_loss: 0.8181	g_loss: 1.9955
Epoch [4/	10]	d_loss: 1.2121	g_loss: 1.3168
Epoch [4/	10]	d_loss: 1.1212	g_loss: 1.8228
Epoch [4/	10]	d_loss: 1.0847	g_loss: 2.0742
Epoch [4/	10]	d_loss: 1.1528	g_loss: 1.3479
Epoch [4/	10]	d_loss: 1.6599	g_loss: 0.9825
Epoch [4/	10]	d_loss: 0.9309	g_loss: 1.4802

Epoch [4/	10]	d_loss: 1.0809	g_loss: 2.2229
Epoch [4/	10]	d_loss: 0.6724	g_loss: 1.3572
Epoch [4/	10]	d_loss: 0.9892	g_loss: 1.6207
Epoch [4/	10]	d_loss: 1.0626	g_loss: 1.1961
Epoch [4/	10]	d_loss: 1.1962	g_loss: 2.0308
Epoch [4/	10]	d_loss: 1.0514	g_loss: 1.1713
Epoch [4/	10]	d_loss: 0.7584	g_loss: 1.4701
Epoch [4/	10]	d_loss: 1.0754	g_loss: 2.1302
Epoch [4/	10]	d_loss: 0.8918	g_loss: 1.6707
Epoch [4/	10]	d_loss: 1.0512	g_loss: 0.9735
Epoch [4/	10]	d_loss: 0.9611	g_loss: 1.2512
Epoch [4/	10]	d_loss: 0.9215	g_loss: 1.8310
Epoch [4/	10]	d_loss: 1.1587	g_loss: 1.6202
Epoch [4/	10]	d_loss: 1.2601	g_loss: 1.2518
Epoch [4/	10]	d_loss: 1.0736	g_loss: 1.3041
Epoch [4/	10]	d_loss: 1.1442	g_loss: 1.5960
Epoch [4/	10]	d_loss: 1.3616	g_loss: 1.1612
Epoch [4/	10]	d_loss: 0.9483	g_loss: 1.2930
Epoch [4/	10]	d_loss: 1.6049	g_loss: 2.5226
Epoch [4/	10]	d_loss: 0.9580	g_loss: 1.1246
Epoch [4/	10]	d_loss: 1.1188	g_loss: 1.8327
Epoch [4/	10]	d_loss: 0.9736	g_loss: 1.2381
Epoch [4/	10]	d_loss: 0.9526	g_loss: 1.5222
Epoch [4/	10]	d_loss: 0.9186	g_loss: 1.2669
Epoch [4/	10]	d_loss: 1.1580	g_loss: 1.4127
Epoch [4/	10]	d_loss: 0.9100	g_loss: 1.6952
Epoch [4/	10]	d_loss: 1.2877	g_loss: 0.9177
Epoch [4/	10]	d_loss: 0.8739	g_loss: 1.9813
Epoch [4/	10]	d_loss: 0.9727	g_loss: 1.9253
Epoch [4/	10]	d_loss: 1.5521	g_loss: 1.7312
Epoch [4/	10]	d_loss: 1.3410	g_loss: 0.6925
Epoch [4/	10]	d_loss: 0.8950	g_loss: 1.3280
Epoch [4/	10]	d_loss: 1.0160	g_loss: 1.6559
Epoch [4/	10]	d_loss: 1.2604	g_loss: 1.5461
Epoch [4/	10]	d_loss: 0.9914	g_loss: 2.6337
Epoch [4/	10]	d_loss: 1.0528	g_loss: 1.1219
Epoch [4/	10]	d_loss: 1.3292	g_loss: 2.5788
Epoch [4/	10]	d_loss: 1.3515	g_loss: 0.9151
Epoch [4/	10]	d_loss: 0.8512	g_loss: 1.3085
Epoch [4/	10]	d_loss: 1.0442	g_loss: 1.5975
Epoch [4/	10]	d_loss: 1.0674	g_loss: 1.5195
Epoch [4/	10]	d_loss: 1.8059	g_loss: 3.2087
Epoch [4/	10]	d_loss: 1.0624	g_loss: 1.5757
Epoch [4/	10]	d_loss: 1.4623	g_loss: 2.0987
Epoch [4/	10]	d_loss: 1.2563	g_loss: 1.0405
Epoch [4/	10]	d_loss: 1.2931	g_loss: 0.6135
Epoch [4/	10]	d_loss: 1.2906	g_loss: 2.1331
Epoch [4/	10]	d_loss: 0.7915	g_loss: 1.8433

Epoch [4/	10]	d_loss: 1.0233	g_loss: 2.3858
Epoch [4/	10]	d_loss: 0.7885	g_loss: 1.6247
Epoch [4/	10]	d_loss: 1.4405	g_loss: 0.9376
Epoch [5/	10]	d_loss: 1.1318	g_loss: 0.9082
Epoch [5/	10]	d_loss: 0.7803	g_loss: 2.4624
Epoch [5/	10]	d_loss: 1.3940	g_loss: 1.0214
Epoch [5/	10]	d_loss: 1.0232	g_loss: 0.9746
Epoch [5/	10]	d_loss: 1.3650	g_loss: 2.6696
Epoch [5/	10]	d_loss: 1.0000	g_loss: 1.8816
Epoch [5/	10]	d_loss: 1.0050	g_loss: 1.1029
Epoch [5/	10]	d_loss: 1.2160	g_loss: 1.9930
Epoch [5/	10]	d_loss: 0.8427	g_loss: 1.6330
Epoch [5/	10]	d_loss: 1.4914	g_loss: 0.7409
Epoch [5/	10]	d_loss: 1.2116	g_loss: 1.1024
Epoch [5/	10]	d_loss: 0.8809	g_loss: 2.1050
Epoch [5/	10]	d_loss: 0.8529	g_loss: 2.4208
Epoch [5/	10]	d_loss: 1.4474	g_loss: 1.6805
Epoch [5/	10]	d_loss: 0.7559	g_loss: 1.8718
Epoch [5/	10]	d_loss: 0.6650	g_loss: 1.8591
Epoch [5/	10]	d_loss: 1.1224	g_loss: 1.0908
Epoch [5/	10]	d_loss: 0.7636	g_loss: 1.7753
Epoch [5/	10]	d_loss: 0.7861	g_loss: 1.7060
Epoch [5/	10]	d_loss: 1.2727	g_loss: 0.9213
Epoch [5/	10]	d_loss: 0.7646	g_loss: 1.9612
Epoch [5/	10]	d_loss: 0.9942	g_loss: 1.1278
Epoch [5/	10]	d_loss: 1.0997	g_loss: 0.8268
Epoch [5/	10]	d_loss: 1.0850	g_loss: 2.2054
Epoch [5/	10]	d_loss: 1.0862	g_loss: 1.0529
Epoch [5/	10]	d_loss: 1.2484	g_loss: 0.8678
Epoch [5/	10]	d_loss: 1.3771	g_loss: 1.5351
Epoch [5/	10]	d_loss: 1.3312	g_loss: 0.9755
Epoch [5/	10]	d_loss: 0.9800	g_loss: 1.8784
Epoch [5/	10]	d_loss: 1.2135	g_loss: 0.8230
Epoch [5/	10]	d_loss: 0.9621	g_loss: 1.5346
Epoch [5/	10]	d_loss: 0.8643	g_loss: 1.6710
Epoch [5/	10]	d_loss: 0.8906	g_loss: 1.3413
Epoch [5/	10]	d_loss: 0.9007	g_loss: 1.1027
Epoch [5/	10]	d_loss: 0.9548	g_loss: 2.4572
Epoch [5/	10]	d_loss: 1.1130	g_loss: 2.3750
Epoch [5/	10]	d_loss: 1.2107	g_loss: 1.1435
Epoch [5/	10]	d_loss: 1.7393	g_loss: 2.8410
Epoch [5/	10]	d_loss: 1.1707	g_loss: 0.7529
Epoch [5/	10]	d_loss: 1.6233	g_loss: 0.9072
Epoch [5/	10]	d_loss: 1.1644	g_loss: 0.6178
Epoch [5/	10]	d_loss: 1.3627	g_loss: 1.1879
Epoch [5/	10]	d_loss: 1.1955	g_loss: 1.0738
Epoch [5/	10]	d_loss: 0.7556	g_loss: 1.6250
Epoch [5/	10]	d_loss: 0.9617	g_loss: 0.8069

Epoch [5/	10]	d_loss: 0.7481	g_loss: 1.2254
Epoch [5/	10]	d_loss: 1.2104	g_loss: 2.6066
Epoch [5/	10]	d_loss: 1.2634	g_loss: 3.0451
Epoch [5/	10]	d_loss: 1.3173	g_loss: 0.4815
Epoch [5/	10]	d_loss: 0.8571	g_loss: 1.2050
Epoch [5/	10]	d_loss: 1.4727	g_loss: 1.4522
Epoch [5/	10]	d_loss: 0.6468	g_loss: 1.6101
Epoch [5/	10]	d_loss: 1.3495	g_loss: 1.7757
Epoch [5/	10]	d_loss: 1.2707	g_loss: 1.0924
Epoch [5/	10]	d_loss: 0.9537	g_loss: 1.0868
Epoch [5/	10]	d_loss: 0.6343	g_loss: 2.1441
Epoch [5/	10]	d_loss: 0.7363	g_loss: 1.4944
Epoch [5/	10]	d_loss: 1.1470	g_loss: 0.8106
Epoch [5/	10]	d_loss: 0.6263	g_loss: 1.8273
Epoch [5/	10]	d_loss: 0.5548	g_loss: 2.3027
Epoch [5/	10]	d_loss: 0.9288	g_loss: 2.1814
Epoch [5/	10]	d_loss: 0.9313	g_loss: 1.8208
Epoch [5/	10]	d_loss: 1.2500	g_loss: 1.9439
Epoch [5/	10]	d_loss: 0.6947	g_loss: 1.5238
Epoch [5/	10]	d_loss: 1.0407	g_loss: 1.5261
Epoch [5/	10]	d_loss: 1.0193	g_loss: 2.3485
Epoch [5/	10]	d_loss: 0.7951	g_loss: 1.1454
Epoch [5/	10]	d_loss: 0.8142	g_loss: 1.9082
Epoch [5/	10]	d_loss: 0.8810	g_loss: 2.6096
Epoch [5/	10]	d_loss: 0.8751	g_loss: 1.4037
Epoch [5/	10]	d_loss: 0.7016	g_loss: 1.9413
Epoch [5/	10]	d_loss: 0.9675	g_loss: 2.4667
Epoch [5/	10]	d_loss: 0.7592	g_loss: 1.3252
Epoch [5/	10]	d_loss: 1.2981	g_loss: 0.8734
Epoch [5/	10]	d_loss: 0.8893	g_loss: 1.9614
Epoch [5/	10]	d_loss: 1.1661	g_loss: 2.2346
Epoch [5/	10]	d_loss: 0.7977	g_loss: 1.3500
Epoch [5/	10]	d_loss: 0.6829	g_loss: 1.7819
Epoch [5/	10]	d_loss: 1.1961	g_loss: 1.6565
Epoch [5/	10]	d_loss: 1.4171	g_loss: 0.8677
Epoch [5/	10]	d_loss: 0.8070	g_loss: 1.1225
Epoch [5/	10]	d_loss: 0.6209	g_loss: 1.8520
Epoch [5/	10]	d_loss: 0.9298	g_loss: 1.7088
Epoch [5/	10]	d_loss: 1.3736	g_loss: 1.7714
Epoch [5/	10]	d_loss: 1.0659	g_loss: 1.4655
Epoch [5/	10]	d_loss: 0.6740	g_loss: 1.4516
Epoch [5/	10]	d_loss: 0.8683	g_loss: 1.6674
Epoch [5/	10]	d_loss: 1.5871	g_loss: 1.8583
Epoch [5/	10]	d_loss: 0.7465	g_loss: 2.1066
Epoch [5/	10]	d_loss: 1.2062	g_loss: 0.7780
Epoch [6/	10]	d_loss: 1.4250	g_loss: 2.7882
Epoch [6/	10]	d_loss: 0.8720	g_loss: 2.6640
Epoch [6/	10]	d_loss: 0.8521	g_loss: 1.1320

Epoch [6/	10]	d_loss: 1.7684	g_loss: 0.5917
Epoch [6/	10]	d_loss: 1.2578	g_loss: 0.8816
Epoch [6/	10]	d_loss: 1.1706	g_loss: 0.8676
Epoch [6/	10]	d_loss: 0.9345	g_loss: 1.7406
Epoch [6/	10]	d_loss: 0.5859	g_loss: 1.6846
Epoch [6/	10]	d_loss: 1.6689	g_loss: 0.9139
Epoch [6/	10]	d_loss: 0.8892	g_loss: 1.7129
Epoch [6/	10]	d_loss: 1.1140	g_loss: 0.9444
Epoch [6/	10]	d_loss: 0.8697	g_loss: 1.6381
Epoch [6/	10]	d_loss: 0.8479	g_loss: 1.9758
Epoch [6/	10]	d_loss: 0.5680	g_loss: 2.3358
Epoch [6/	10]	d_loss: 1.2702	g_loss: 1.5182
Epoch [6/	10]	d_loss: 1.0473	g_loss: 1.3541
Epoch [6/	10]	d_loss: 0.7378	g_loss: 1.1823
Epoch [6/	10]	d_loss: 0.8861	g_loss: 1.7672
Epoch [6/	10]	d_loss: 1.4007	g_loss: 2.3100
Epoch [6/	10]	d_loss: 1.2109	g_loss: 1.1629
Epoch [6/	10]	d_loss: 1.0677	g_loss: 1.2983
Epoch [6/	10]	d_loss: 0.9102	g_loss: 2.3185
Epoch [6/	10]	d_loss: 1.5296	g_loss: 0.8756
Epoch [6/	10]	d_loss: 0.7984	g_loss: 2.0042
Epoch [6/	10]	d_loss: 1.3222	g_loss: 0.4767
Epoch [6/	10]	d_loss: 1.0952	g_loss: 1.8266
Epoch [6/	10]	d_loss: 0.8410	g_loss: 1.8611
Epoch [6/	10]	d_loss: 1.3753	g_loss: 1.4048
Epoch [6/	10]	d_loss: 1.4978	g_loss: 0.7934
Epoch [6/	10]	d_loss: 1.1181	g_loss: 1.8696
Epoch [6/	10]	d_loss: 1.0634	g_loss: 2.5611
Epoch [6/	10]	d_loss: 0.6618	g_loss: 2.7094
Epoch [6/	10]	d_loss: 0.8346	g_loss: 1.0999
Epoch [6/	10]	d_loss: 0.8691	g_loss: 3.3966
Epoch [6/	10]	d_loss: 0.8672	g_loss: 1.5879
Epoch [6/	10]	d_loss: 0.9509	g_loss: 1.4326
Epoch [6/	10]	d_loss: 0.9790	g_loss: 2.4175
Epoch [6/	10]	d_loss: 1.1414	g_loss: 1.1430
Epoch [6/	10]	d_loss: 1.0889	g_loss: 1.3757
Epoch [6/	10]	d_loss: 0.7713	g_loss: 2.1558
Epoch [6/	10]	d_loss: 1.0888	g_loss: 0.7501
Epoch [6/	10]	d_loss: 0.9294	g_loss: 1.4335
Epoch [6/	10]	d_loss: 0.9770	g_loss: 1.5831
Epoch [6/	10]	d_loss: 0.7698	g_loss: 1.2390
Epoch [6/	10]	d_loss: 1.2482	g_loss: 0.9524
Epoch [6/	10]	d_loss: 1.3267	g_loss: 1.6403
Epoch [6/	10]	d_loss: 0.6662	g_loss: 1.4787
Epoch [6/	10]	d_loss: 1.4592	g_loss: 3.4445
Epoch [6/	10]	d_loss: 0.9540	g_loss: 1.4721
Epoch [6/	10]	d_loss: 1.1247	g_loss: 1.7337
Epoch [6/	10]	d_loss: 0.7378	g_loss: 1.2276

Epoch [6/	10]	d_loss: 1.1816	g_loss: 2.7881
Epoch [6/	10]	d_loss: 0.8952	g_loss: 1.3970
Epoch [6/	10]	d_loss: 0.5914	g_loss: 1.3719
Epoch [6/	10]	d_loss: 0.6932	g_loss: 1.5376
Epoch [6/	10]	d_loss: 0.8033	g_loss: 1.3559
Epoch [6/	10]	d_loss: 0.6146	g_loss: 1.4037
Epoch [6/	10]	d_loss: 0.7671	g_loss: 1.8319
Epoch [6/	10]	d_loss: 1.3831	g_loss: 1.1665
Epoch [6/	10]	d_loss: 1.2877	g_loss: 2.7399
Epoch [6/	10]	d_loss: 1.0341	g_loss: 1.0020
Epoch [6/	10]	d_loss: 1.5644	g_loss: 2.4344
Epoch [6/	10]	d_loss: 1.0648	g_loss: 1.4189
Epoch [6/	10]	d_loss: 0.5959	g_loss: 1.3869
Epoch [6/	10]	d_loss: 1.0660	g_loss: 1.5331
Epoch [6/	10]	d_loss: 1.1338	g_loss: 0.6853
Epoch [6/	10]	d_loss: 0.9550	g_loss: 1.2980
Epoch [6/	10]	d_loss: 0.8976	g_loss: 1.2840
Epoch [6/	10]	d_loss: 1.0090	g_loss: 0.9045
Epoch [6/	10]	d_loss: 0.5004	g_loss: 2.7501
Epoch [6/	10]	d_loss: 1.1630	g_loss: 1.3988
Epoch [6/	10]	d_loss: 0.7619	g_loss: 2.0980
Epoch [6/	10]	d_loss: 1.2471	g_loss: 1.1085
Epoch [6/	10]	d_loss: 0.9637	g_loss: 1.0797
Epoch [6/	10]	d_loss: 0.9734	g_loss: 1.0593
Epoch [6/	10]	d_loss: 1.1911	g_loss: 0.9331
Epoch [6/	10]	d_loss: 1.1212	g_loss: 1.2914
Epoch [6/	10]	d_loss: 0.7436	g_loss: 1.5432
Epoch [6/	10]	d_loss: 0.9698	g_loss: 1.7825
Epoch [6/	10]	d_loss: 0.9088	g_loss: 0.7057
Epoch [6/	10]	d_loss: 0.7578	g_loss: 1.9996
Epoch [6/	10]	d_loss: 0.7167	g_loss: 1.6305
Epoch [6/	10]	d_loss: 0.7271	g_loss: 2.4807
Epoch [6/	10]	d_loss: 0.8660	g_loss: 1.7858
Epoch [6/	10]	d_loss: 1.6879	g_loss: 1.6712
Epoch [6/	10]	d_loss: 1.3331	g_loss: 2.4035
Epoch [6/	10]	d_loss: 0.8148	g_loss: 0.9077
Epoch [6/	10]	d_loss: 1.0730	g_loss: 1.9865
Epoch [6/	10]	d_loss: 1.1134	g_loss: 2.2211
Epoch [6/	10]	d_loss: 0.7743	g_loss: 1.3932
Epoch [7/	10]	d_loss: 0.9832	g_loss: 1.2389
Epoch [7/	10]	d_loss: 1.3259	g_loss: 1.3239
Epoch [7/	10]	d_loss: 0.8246	g_loss: 1.1267
Epoch [7/	10]	d_loss: 0.5303	g_loss: 2.1189
Epoch [7/	10]	d_loss: 0.6017	g_loss: 1.4290
Epoch [7/	10]	d_loss: 0.9810	g_loss: 0.6529
Epoch [7/	10]	d_loss: 0.9017	g_loss: 1.6018
Epoch [7/	10]	d_loss: 0.9937	g_loss: 1.1704
Epoch [7/	10]	d_loss: 0.7347	g_loss: 1.5510

Epoch [7/	10]	d_loss: 1.2292	g_loss: 1.6607
Epoch [7/	10]	d_loss: 0.8850	g_loss: 0.9888
Epoch [7/	10]	d_loss: 1.1096	g_loss: 1.0860
Epoch [7/	10]	d_loss: 0.8570	g_loss: 1.4345
Epoch [7/	10]	d_loss: 0.5851	g_loss: 3.0706
Epoch [7/	10]	d_loss: 1.3173	g_loss: 1.3844
Epoch [7/	10]	d_loss: 1.0054	g_loss: 1.4896
Epoch [7/	10]	d_loss: 0.6089	g_loss: 2.2562
Epoch [7/	10]	d_loss: 1.1886	g_loss: 2.3746
Epoch [7/	10]	d_loss: 0.9191	g_loss: 2.2482
Epoch [7/	10]	d_loss: 1.3633	g_loss: 2.7447
Epoch [7/	10]	d_loss: 1.0784	g_loss: 1.1613
Epoch [7/	10]	d_loss: 0.5889	g_loss: 2.4379
Epoch [7/	10]	d_loss: 0.8633	g_loss: 1.0314
Epoch [7/	10]	d_loss: 0.9013	g_loss: 1.9624
Epoch [7/	10]	d_loss: 0.9309	g_loss: 0.7054
Epoch [7/	10]	d_loss: 1.0756	g_loss: 1.7590
Epoch [7/	10]	d_loss: 1.2922	g_loss: 2.1340
Epoch [7/	10]	d_loss: 1.5976	g_loss: 1.0648
Epoch [7/	10]	d_loss: 0.8383	g_loss: 2.4233
Epoch [7/	10]	d_loss: 0.7406	g_loss: 1.5595
Epoch [7/	10]	d_loss: 1.6125	g_loss: 1.3186
Epoch [7/	10]	d_loss: 1.0481	g_loss: 1.7933
Epoch [7/	10]	d_loss: 0.5137	g_loss: 2.9293
Epoch [7/	10]	d_loss: 0.8022	g_loss: 1.3955
Epoch [7/	10]	d_loss: 0.6655	g_loss: 1.6284
Epoch [7/	10]	d_loss: 1.2457	g_loss: 0.8281
Epoch [7/	10]	d_loss: 1.4008	g_loss: 3.0965
Epoch [7/	10]	d_loss: 0.7079	g_loss: 1.2935
Epoch [7/	10]	d_loss: 0.8799	g_loss: 1.2394
Epoch [7/	10]	d_loss: 0.8600	g_loss: 2.4117
Epoch [7/	10]	d_loss: 1.2369	g_loss: 1.6762
Epoch [7/	10]	d_loss: 0.7410	g_loss: 2.6945
Epoch [7/	10]	d_loss: 0.8873	g_loss: 2.2021
Epoch [7/	10]	d_loss: 1.2878	g_loss: 1.2701
Epoch [7/	10]	d_loss: 0.7389	g_loss: 2.1464
Epoch [7/	10]	d_loss: 0.8881	g_loss: 1.8859
Epoch [7/	10]	d_loss: 0.6638	g_loss: 2.1203
Epoch [7/	10]	d_loss: 0.9131	g_loss: 1.7972
Epoch [7/	10]	d_loss: 0.8611	g_loss: 1.4104
Epoch [7/	10]	d_loss: 0.8724	g_loss: 1.7404
Epoch [7/	10]	d_loss: 0.8577	g_loss: 1.3647
Epoch [7/	10]	d_loss: 1.1319	g_loss: 1.1247
Epoch [7/	10]	d_loss: 0.9180	g_loss: 2.5746
Epoch [7/	10]	d_loss: 0.6490	g_loss: 2.1792
Epoch [7/	10]	d_loss: 0.9730	g_loss: 2.3709
Epoch [7/	10]	d_loss: 1.1422	g_loss: 1.7629
Epoch [7/	10]	d_loss: 1.0092	g_loss: 1.3433

Epoch [7/	10]	d_loss: 1.2869	g_loss: 1.4783
Epoch [7/	10]	d_loss: 0.7989	g_loss: 1.5123
Epoch [7/	10]	d_loss: 1.0054	g_loss: 2.4025
Epoch [7/	10]	d_loss: 0.9099	g_loss: 1.2777
Epoch [7/	10]	d_loss: 0.8845	g_loss: 1.8346
Epoch [7/	10]	d_loss: 1.1272	g_loss: 2.0638
Epoch [7/	10]	d_loss: 0.9431	g_loss: 1.5864
Epoch [7/	10]	d_loss: 1.0458	g_loss: 3.8013
Epoch [7/	10]	d_loss: 1.0771	g_loss: 1.3579
Epoch [7/	10]	d_loss: 1.7283	g_loss: 1.9654
Epoch [7/	10]	d_loss: 0.9469	g_loss: 2.1977
Epoch [7/	10]	d_loss: 0.8162	g_loss: 2.6007
Epoch [7/	10]	d_loss: 1.1781	g_loss: 1.3534
Epoch [7/	10]	d_loss: 0.9052	g_loss: 1.4187
Epoch [7/	10]	d_loss: 1.8337	g_loss: 0.7132
Epoch [7/	10]	d_loss: 0.9595	g_loss: 1.4336
Epoch [7/	10]	d_loss: 0.7851	g_loss: 2.0970
Epoch [7/	10]	d_loss: 0.6954	g_loss: 2.3723
Epoch [7/	10]	d_loss: 1.0225	g_loss: 2.5177
Epoch [7/	10]	d_loss: 0.6899	g_loss: 1.1928
Epoch [7/	10]	d_loss: 1.1289	g_loss: 0.8644
Epoch [7/	10]	d_loss: 0.7559	g_loss: 1.4595
Epoch [7/	10]	d_loss: 0.8719	g_loss: 1.1070
Epoch [7/	10]	d_loss: 0.9614	g_loss: 2.7570
Epoch [7/	10]	d_loss: 0.8925	g_loss: 2.1880
Epoch [7/	10]	d_loss: 0.7354	g_loss: 1.1059
Epoch [7/	10]	d_loss: 0.7620	g_loss: 1.0141
Epoch [7/	10]	d_loss: 0.8771	g_loss: 1.7345
Epoch [7/	10]	d_loss: 0.6950	g_loss: 2.1624
Epoch [7/	10]	d_loss: 1.0692	g_loss: 1.9985
Epoch [7/	10]	d_loss: 0.6484	g_loss: 1.7117
Epoch [7/	10]	d_loss: 1.0777	g_loss: 1.7878
Epoch [7/	10]	d_loss: 0.9225	g_loss: 2.1554
Epoch [8/	10]	d_loss: 0.7918	g_loss: 2.1960
Epoch [8/	10]	d_loss: 1.0478	g_loss: 1.9607
Epoch [8/	10]	d_loss: 1.1279	g_loss: 2.5284
Epoch [8/	10]	d_loss: 0.7861	g_loss: 1.8285
Epoch [8/	10]	d_loss: 1.0051	g_loss: 0.9922
Epoch [8/	10]	d_loss: 0.5010	g_loss: 2.0198
Epoch [8/	10]	d_loss: 1.5435	g_loss: 1.2359
Epoch [8/	10]	d_loss: 0.7558	g_loss: 2.1014
Epoch [8/	10]	d_loss: 1.0910	g_loss: 1.1916
Epoch [8/	10]	d_loss: 1.1795	g_loss: 1.1372
Epoch [8/	10]	d_loss: 0.7634	g_loss: 1.4697
Epoch [8/	10]	d_loss: 0.6715	g_loss: 0.8878
Epoch [8/	10]	d_loss: 0.6140	g_loss: 2.0526
Epoch [8/	10]	d_loss: 1.4654	g_loss: 0.8190
Epoch [8/	10]	d_loss: 0.7186	g_loss: 2.0784

Epoch [8/	10]	d_loss: 1.2983	g_loss: 1.9815
Epoch [8/	10]	d_loss: 1.3141	g_loss: 2.0868
Epoch [8/	10]	d_loss: 0.9343	g_loss: 1.0632
Epoch [8/	10]	d_loss: 1.0339	g_loss: 3.0128
Epoch [8/	10]	d_loss: 0.7546	g_loss: 2.3286
Epoch [8/	10]	d_loss: 0.7908	g_loss: 1.8858
Epoch [8/	10]	d_loss: 1.1077	g_loss: 1.1247
Epoch [8/	10]	d_loss: 0.7954	g_loss: 2.3514
Epoch [8/	10]	d_loss: 1.4524	g_loss: 0.9789
Epoch [8/	10]	d_loss: 0.8086	g_loss: 1.3136
Epoch [8/	10]	d_loss: 0.6421	g_loss: 2.8472
Epoch [8/	10]	d_loss: 1.0943	g_loss: 1.7574
Epoch [8/	10]	d_loss: 0.8612	g_loss: 2.7814
Epoch [8/	10]	d_loss: 1.1405	g_loss: 1.9476
Epoch [8/	10]	d_loss: 0.8273	g_loss: 1.6878
Epoch [8/	10]	d_loss: 0.8735	g_loss: 2.8736
Epoch [8/	10]	d_loss: 0.4872	g_loss: 2.3515
Epoch [8/	10]	d_loss: 0.6194	g_loss: 2.6196
Epoch [8/	10]	d_loss: 0.6052	g_loss: 2.1412
Epoch [8/	10]	d_loss: 1.2355	g_loss: 1.2913
Epoch [8/	10]	d_loss: 0.6816	g_loss: 1.4983
Epoch [8/	10]	d_loss: 0.8024	g_loss: 2.5858
Epoch [8/	10]	d_loss: 1.0933	g_loss: 3.6184
Epoch [8/	10]	d_loss: 1.0110	g_loss: 3.1034
Epoch [8/	10]	d_loss: 0.7571	g_loss: 1.9247
Epoch [8/	10]	d_loss: 0.8880	g_loss: 2.6252
Epoch [8/	10]	d_loss: 1.0039	g_loss: 1.5612
Epoch [8/	10]	d_loss: 1.0183	g_loss: 1.9759
Epoch [8/	10]	d_loss: 0.9224	g_loss: 2.8940
Epoch [8/	10]	d_loss: 0.6854	g_loss: 2.2664
Epoch [8/	10]	d_loss: 0.7670	g_loss: 2.2917
Epoch [8/	10]	d_loss: 0.5354	g_loss: 1.3654
Epoch [8/	10]	d_loss: 0.9835	g_loss: 1.3671
Epoch [8/	10]	d_loss: 0.6889	g_loss: 2.5114
Epoch [8/	10]	d_loss: 1.2708	g_loss: 2.4359
Epoch [8/	10]	d_loss: 0.9924	g_loss: 1.7111
Epoch [8/	10]	d_loss: 0.8324	g_loss: 2.5917
Epoch [8/	10]	d_loss: 0.5919	g_loss: 2.8174
Epoch [8/	10]	d_loss: 0.6137	g_loss: 1.8088
Epoch [8/	10]	d_loss: 0.7334	g_loss: 1.4561
Epoch [8/	10]	d_loss: 1.0133	g_loss: 1.2435
Epoch [8/	10]	d_loss: 1.3144	g_loss: 2.8424
Epoch [8/	10]	d_loss: 1.1627	g_loss: 1.3109
Epoch [8/	10]	d_loss: 0.9726	g_loss: 1.8123
Epoch [8/	10]	d_loss: 1.3089	g_loss: 3.5324
Epoch [8/	10]	d_loss: 1.0461	g_loss: 0.8428
Epoch [8/	10]	d_loss: 0.8196	g_loss: 1.9199
Epoch [8/	10]	d_loss: 0.9176	g_loss: 1.1626

Epoch [8/	10]	d_loss: 0.5924	g_loss: 1.6474
Epoch [8/	10]	d_loss: 0.8787	g_loss: 0.9900
Epoch [8/	10]	d_loss: 0.8035	g_loss: 1.2505
Epoch [8/	10]	d_loss: 1.0451	g_loss: 2.1737
Epoch [8/	10]	d_loss: 0.9598	g_loss: 0.9274
Epoch [8/	10]	d_loss: 0.6745	g_loss: 2.0649
Epoch [8/	10]	d_loss: 0.6283	g_loss: 1.6901
Epoch [8/	10]	d_loss: 1.4618	g_loss: 2.9967
Epoch [8/	10]	d_loss: 1.0357	g_loss: 3.2163
Epoch [8/	10]	d_loss: 0.9631	g_loss: 2.5392
Epoch [8/	10]	d_loss: 1.2619	g_loss: 2.4341
Epoch [8/	10]	d_loss: 1.0154	g_loss: 0.7984
Epoch [8/	10]	d_loss: 0.7701	g_loss: 1.4395
Epoch [8/	10]	d_loss: 1.1962	g_loss: 2.8623
Epoch [8/	10]	d_loss: 0.7117	g_loss: 2.2822
Epoch [8/	10]	d_loss: 1.3575	g_loss: 0.8509
Epoch [8/	10]	d_loss: 1.1333	g_loss: 1.6819
Epoch [8/	10]	d_loss: 0.9081	g_loss: 1.5477
Epoch [8/	10]	d_loss: 0.6987	g_loss: 1.3661
Epoch [8/	10]	d_loss: 0.9038	g_loss: 2.4889
Epoch [8/	10]	d_loss: 1.1444	g_loss: 1.6110
Epoch [8/	10]	d_loss: 0.9373	g_loss: 1.8816
Epoch [8/	10]	d_loss: 0.9983	g_loss: 2.2010
Epoch [8/	10]	d_loss: 1.6550	g_loss: 1.3623
Epoch [8/	10]	d_loss: 1.0981	g_loss: 3.7121
Epoch [8/	10]	d_loss: 0.7028	g_loss: 1.6321
Epoch [8/	10]	d_loss: 0.7153	g_loss: 2.4977
Epoch [9/	10]	d_loss: 0.7606	g_loss: 1.9253
Epoch [9/	10]	d_loss: 0.5026	g_loss: 2.3842
Epoch [9/	10]	d_loss: 0.8090	g_loss: 0.9323
Epoch [9/	10]	d_loss: 0.5941	g_loss: 2.0908
Epoch [9/	10]	d_loss: 0.6804	g_loss: 1.5060
Epoch [9/	10]	d_loss: 0.8574	g_loss: 1.7809
Epoch [9/	10]	d_loss: 1.7079	g_loss: 2.9482
Epoch [9/	10]	d_loss: 1.0217	g_loss: 1.7747
Epoch [9/	10]	d_loss: 1.0875	g_loss: 3.0244
Epoch [9/	10]	d_loss: 0.8915	g_loss: 2.8352
Epoch [9/	10]	d_loss: 0.6787	g_loss: 2.0770
Epoch [9/	10]	d_loss: 0.9768	g_loss: 2.9597
Epoch [9/	10]	d_loss: 0.8458	g_loss: 1.1887
Epoch [9/	10]	d_loss: 1.0741	g_loss: 2.1457
Epoch [9/	10]	d_loss: 0.6579	g_loss: 2.5003
Epoch [9/	10]	d_loss: 0.4908	g_loss: 3.3861
Epoch [9/	10]	d_loss: 0.4882	g_loss: 2.0469
Epoch [9/	10]	d_loss: 0.5985	g_loss: 0.9357
Epoch [9/	10]	d_loss: 0.7202	g_loss: 1.6967
Epoch [9/	10]	d_loss: 0.7003	g_loss: 1.7794
Epoch [9/	10]	d_loss: 0.6105	g_loss: 3.1953

Epoch [9/	10]	d_loss: 0.9430	g_loss: 1.4835
Epoch [9/	10]	d_loss: 0.6438	g_loss: 3.0813
Epoch [9/	10]	d_loss: 1.2055	g_loss: 1.8407
Epoch [9/	10]	d_loss: 1.1846	g_loss: 1.6896
Epoch [9/	10]	d_loss: 1.3750	g_loss: 3.1959
Epoch [9/	10]	d_loss: 0.6124	g_loss: 3.1329
Epoch [9/	10]	d_loss: 1.1733	g_loss: 0.9527
Epoch [9/	10]	d_loss: 0.9037	g_loss: 1.9663
Epoch [9/	10]	d_loss: 2.0347	g_loss: 1.1053
Epoch [9/	10]	d_loss: 0.6775	g_loss: 2.2646
Epoch [9/	10]	d_loss: 0.8172	g_loss: 1.7777
Epoch [9/	10]	d_loss: 1.0211	g_loss: 2.5591
Epoch [9/	10]	d_loss: 0.5846	g_loss: 2.8619
Epoch [9/	10]	d_loss: 0.8351	g_loss: 1.6022
Epoch [9/	10]	d_loss: 0.7741	g_loss: 2.6813
Epoch [9/	10]	d_loss: 1.0193	g_loss: 1.8472
Epoch [9/	10]	d_loss: 0.6882	g_loss: 2.4203
Epoch [9/	10]	d_loss: 1.1589	g_loss: 1.9986
Epoch [9/	10]	d_loss: 1.4498	g_loss: 1.6908
Epoch [9/	10]	d_loss: 0.9927	g_loss: 1.5666
Epoch [9/	10]	d_loss: 1.7342	g_loss: 2.6329
Epoch [9/	10]	d_loss: 0.6813	g_loss: 2.9540
Epoch [9/	10]	d_loss: 0.9815	g_loss: 2.3408
Epoch [9/	10]	d_loss: 0.4962	g_loss: 2.5424
Epoch [9/	10]	d_loss: 0.8681	g_loss: 2.0602
Epoch [9/	10]	d_loss: 0.7733	g_loss: 1.8563
Epoch [9/	10]	d_loss: 0.5494	g_loss: 1.9303
Epoch [9/	10]	d_loss: 0.7201	g_loss: 1.8798
Epoch [9/	10]	d_loss: 0.7505	g_loss: 1.5502
Epoch [9/	10]	d_loss: 0.9644	g_loss: 3.0160
Epoch [9/	10]	d_loss: 0.7080	g_loss: 2.9744
Epoch [9/	10]	d_loss: 0.8232	g_loss: 1.9664
Epoch [9/	10]	d_loss: 0.8325	g_loss: 2.3467
Epoch [9/	10]	d_loss: 0.8721	g_loss: 1.2859
Epoch [9/	10]	d_loss: 0.9628	g_loss: 1.7637
Epoch [9/	10]	d_loss: 0.9137	g_loss: 1.2927
Epoch [9/	10]	d_loss: 1.1996	g_loss: 1.0110
Epoch [9/	10]	d_loss: 1.0410	g_loss: 1.3981
Epoch [9/	10]	d_loss: 0.9457	g_loss: 1.3803
Epoch [9/	10]	d_loss: 0.8360	g_loss: 3.8459
Epoch [9/	10]	d_loss: 0.7127	g_loss: 2.0064
Epoch [9/	10]	d_loss: 0.6244	g_loss: 1.6841
Epoch [9/	10]	d_loss: 0.6709	g_loss: 1.9345
Epoch [9/	10]	d_loss: 1.0170	g_loss: 1.6227
Epoch [9/	10]	d_loss: 1.5996	g_loss: 0.9937
Epoch [9/	10]	d_loss: 0.8264	g_loss: 1.8016
Epoch [9/	10]	d_loss: 1.4382	g_loss: 0.6305
Epoch [9/	10]	d_loss: 1.1940	g_loss: 1.3615

Epoch [9/	10]	d_loss: 0.8549	g_loss: 1.7473
Epoch [9/	10]	d_loss: 1.0550	g_loss: 1.6313
Epoch [9/	10]	d_loss: 0.8641	g_loss: 2.6841
Epoch [9/	10]	d_loss: 0.7676	g_loss: 1.4875
Epoch [9/	10]	d_loss: 0.8102	g_loss: 1.9931
Epoch [9/	10]	d_loss: 1.0009	g_loss: 1.1767
Epoch [9/	10]	d_loss: 0.5766	g_loss: 1.3928
Epoch [9/	10]	d_loss: 0.8951	g_loss: 1.9705
Epoch [9/	10]	d_loss: 0.5066	g_loss: 1.5311
Epoch [9/	10]	d_loss: 0.5723	g_loss: 2.0845
Epoch [9/	10]	d_loss: 0.7193	g_loss: 1.4589
Epoch [9/	10]	d_loss: 0.6093	g_loss: 1.8789
Epoch [9/	10]	d_loss: 1.4843	g_loss: 1.5149
Epoch [9/	10]	d_loss: 1.0875	g_loss: 1.5127
Epoch [9/	10]	d_loss: 0.7980	g_loss: 1.4533
Epoch [9/	10]	d_loss: 0.6097	g_loss: 1.3206
Epoch [9/	10]	d_loss: 1.2009	g_loss: 1.8586
Epoch [9/	10]	d_loss: 0.8661	g_loss: 2.1951
Epoch [9/	10]	d_loss: 1.0333	g_loss: 2.0485
Epoch [9/	10]	d_loss: 0.8903	g_loss: 0.7065
Epoch [9/	10]	d_loss: 0.7936	g_loss: 1.5751
Epoch [10/	10]	d_loss: 0.9406	g_loss: 2.7488
Epoch [10/	10]	d_loss: 0.9576	g_loss: 1.7243
Epoch [10/	10]	d_loss: 0.9135	g_loss: 1.6217
Epoch [10/	10]	d_loss: 0.7289	g_loss: 1.9270
Epoch [10/	10]	d_loss: 0.5733	g_loss: 1.5898
Epoch [10/	10]	d_loss: 0.9050	g_loss: 1.9918
Epoch [10/	10]	d_loss: 1.1455	g_loss: 2.1894
Epoch [10/	10]	d_loss: 1.3563	g_loss: 1.5630
Epoch [10/	10]	d_loss: 0.8272	g_loss: 2.6491
Epoch [10/	10]	d_loss: 0.6754	g_loss: 1.8610
Epoch [10/	10]	d_loss: 0.8615	g_loss: 2.4417
Epoch [10/	10]	d_loss: 0.9485	g_loss: 1.0264
Epoch [10/	10]	d_loss: 0.6942	g_loss: 1.1883
Epoch [10/	10]	d_loss: 0.6531	g_loss: 2.1462
Epoch [10/	10]	d_loss: 0.6973	g_loss: 2.7918
Epoch [10/	10]	d_loss: 1.1941	g_loss: 3.5123
Epoch [10/	10]	d_loss: 0.6670	g_loss: 1.7770
Epoch [10/	10]	d_loss: 0.8500	g_loss: 3.0427
Epoch [10/	10]	d_loss: 1.1184	g_loss: 2.6594
Epoch [10/	10]	d_loss: 0.7401	g_loss: 2.3154
Epoch [10/	10]	d_loss: 0.8726	g_loss: 1.0813
Epoch [10/	10]	d_loss: 0.9633	g_loss: 1.9611
Epoch [10/	10]	d_loss: 1.0688	g_loss: 3.4147
Epoch [10/	10]	d_loss: 1.5055	g_loss: 2.7259
Epoch [10/	10]	d_loss: 0.7492	g_loss: 1.8062
Epoch [10/	10]	d_loss: 0.9444	g_loss: 3.0584
Epoch [10/	10]	d_loss: 0.9860	g_loss: 2.2958

Epoch [10/	10]	d_loss: 0.9785	g_loss: 1.2940
Epoch [10/	10]	d_loss: 0.9268	g_loss: 2.0435
Epoch [10/	10]	d_loss: 0.9004	g_loss: 3.9172
Epoch [10/	10]	d_loss: 0.9093	g_loss: 1.2837
Epoch [10/	10]	d_loss: 0.5568	g_loss: 2.2053
Epoch [10/	10]	d_loss: 0.8664	g_loss: 1.8986
Epoch [10/	10]	d_loss: 0.9719	g_loss: 1.8358
Epoch [10/	10]	d_loss: 0.8021	g_loss: 1.3541
Epoch [10/	10]	d_loss: 0.9600	g_loss: 1.9109
Epoch [10/	10]	d_loss: 1.0693	g_loss: 1.6508
Epoch [10/	10]	d_loss: 0.5700	g_loss: 1.9503
Epoch [10/	10]	d_loss: 0.7307	g_loss: 1.7985
Epoch [10/	10]	d_loss: 0.6426	g_loss: 2.3221
Epoch [10/	10]	d_loss: 0.5455	g_loss: 1.6468
Epoch [10/	10]	d_loss: 0.8292	g_loss: 2.6325
Epoch [10/	10]	d_loss: 0.6854	g_loss: 1.3032
Epoch [10/	10]	d_loss: 0.7969	g_loss: 1.4057
Epoch [10/	10]	d_loss: 0.9978	g_loss: 2.0570
Epoch [10/	10]	d_loss: 0.4787	g_loss: 2.6910
Epoch [10/	10]	d_loss: 1.2138	g_loss: 1.0740
Epoch [10/	10]	d_loss: 0.7269	g_loss: 1.6942
Epoch [10/	10]	d_loss: 0.7723	g_loss: 1.9335
Epoch [10/	10]	d_loss: 0.7599	g_loss: 2.2494
Epoch [10/	10]	d_loss: 0.9096	g_loss: 2.2536
Epoch [10/	10]	d_loss: 0.8299	g_loss: 4.0770
Epoch [10/	10]	d_loss: 0.8464	g_loss: 1.4656
Epoch [10/	10]	d_loss: 1.6105	g_loss: 2.0340
Epoch [10/	10]	d_loss: 0.8878	g_loss: 3.7235
Epoch [10/	10]	d_loss: 0.8360	g_loss: 1.1480
Epoch [10/	10]	d_loss: 0.6850	g_loss: 1.8707
Epoch [10/	10]	d_loss: 0.8421	g_loss: 1.8218
Epoch [10/	10]	d_loss: 0.8911	g_loss: 3.8742
Epoch [10/	10]	d_loss: 0.7242	g_loss: 2.0084
Epoch [10/	10]	d_loss: 0.7232	g_loss: 2.7728
Epoch [10/	10]	d_loss: 0.8939	g_loss: 2.3327
Epoch [10/	10]	d_loss: 0.5396	g_loss: 1.8506
Epoch [10/	10]	d_loss: 0.8033	g_loss: 1.7955
Epoch [10/	10]	d_loss: 0.7645	g_loss: 3.2570
Epoch [10/	10]	d_loss: 0.5677	g_loss: 2.8280
Epoch [10/	10]	d_loss: 0.7155	g_loss: 1.2804
Epoch [10/	10]	d_loss: 0.5471	g_loss: 2.6488
Epoch [10/	10]	d_loss: 1.4045	g_loss: 3.0037
Epoch [10/	10]	d_loss: 1.0053	g_loss: 2.3222
Epoch [10/	10]	d_loss: 0.6380	g_loss: 1.2978
Epoch [10/	10]	d_loss: 1.1008	g_loss: 1.7858
Epoch [10/	10]	d_loss: 0.8840	g_loss: 1.3930
Epoch [10/	10]	d_loss: 0.7378	g_loss: 1.6578
Epoch [10/	10]	d_loss: 1.0001	g_loss: 1.4578

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Epoch [ 10/ 10] | d_loss: 0.6269 | g_loss: 3.2813
Epoch [ 10/ 10] | d_loss: 0.7211 | g_loss: 3.1330
Epoch [ 10/ 10] | d_loss: 0.7783 | g_loss: 1.2105
Epoch [ 10/ 10] | d_loss: 0.7884 | g_loss: 1.1184
Epoch [ 10/ 10] | d_loss: 1.4769 | g_loss: 1.6394
Epoch [ 10/ 10] | d_loss: 2.0494 | g_loss: 0.7895
Epoch [ 10/ 10] | d_loss: 1.2950 | g_loss: 2.1676
Epoch [ 10/ 10] | d_loss: 1.0184 | g_loss: 1.4635
Epoch [ 10/ 10] | d_loss: 0.5696 | g_loss: 2.1593
Epoch [ 10/ 10] | d_loss: 0.6495 | g_loss: 1.5507
Epoch [ 10/ 10] | d_loss: 0.8057 | g_loss: 1.9277
Epoch [ 10/ 10] | d_loss: 1.1067 | g_loss: 2.1201
Epoch [ 10/ 10] | d_loss: 0.9305 | g_loss: 0.8883
Epoch [ 10/ 10] | d_loss: 0.6657 | g_loss: 1.8341
Epoch [ 10/ 10] | d_loss: 1.0595 | g_loss: 1.5959

```

2.9 Training loss

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

```

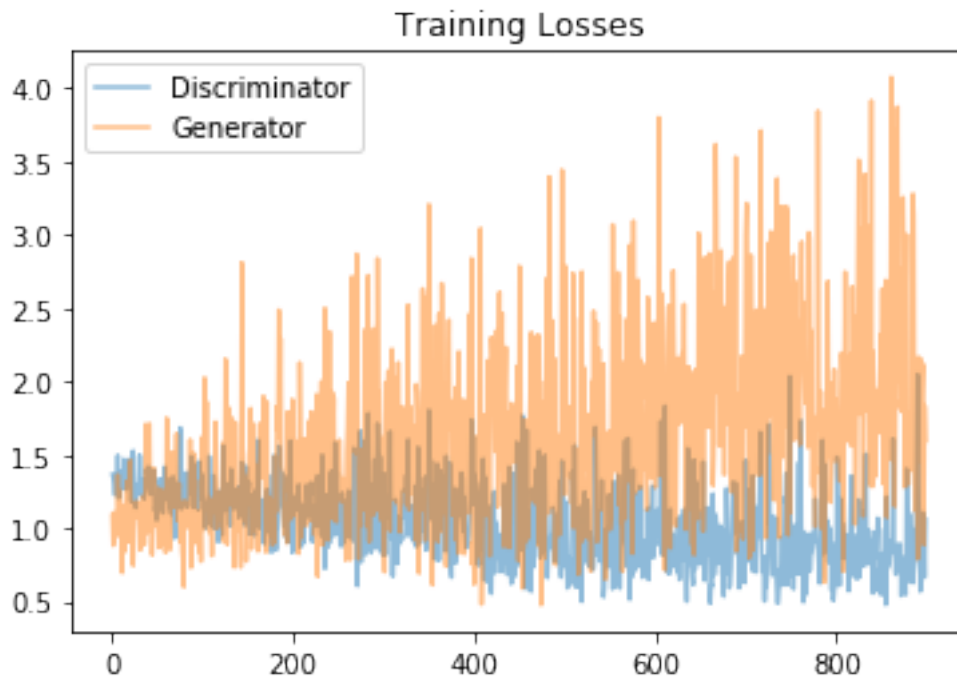
In [51]: fig, ax = plt.subplots()
         losses = np.array(losses)
         plt.plot(losses.T[0], label='Discriminator', alpha=0.5)
         plt.plot(losses.T[1], label='Generator', alpha=0.5)
         plt.title("Training Losses")
         plt.legend()

```

```

Out[51]: <matplotlib.legend.Legend at 0x7fe66439ccc0>

```



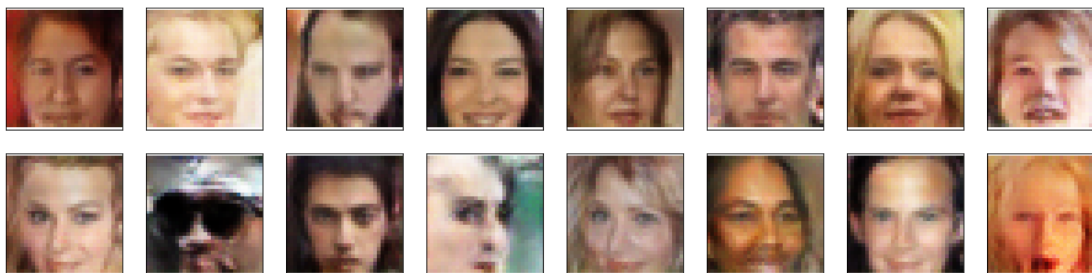
2.10 Generator samples from training

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

```
In [52]: # 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 [53]: # Load samples from generator, taken while training
with open('train_samples.pkl', 'rb') as f:
    samples = pkl.load(f)

In [54]: _ = view_samples(-1, samples)
```



2.10.1 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: - 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 0.5 and it generated more types of faces than beta1 0.1 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.

2.10.2 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.