

dlnd_face_generation

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

```
In [2]: 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 [3]: # necessary imports
```

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

```
In [4]: 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, shuffle=True)

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 [5]: # Define function hyperparameters
        batch_size = 32
        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.

```

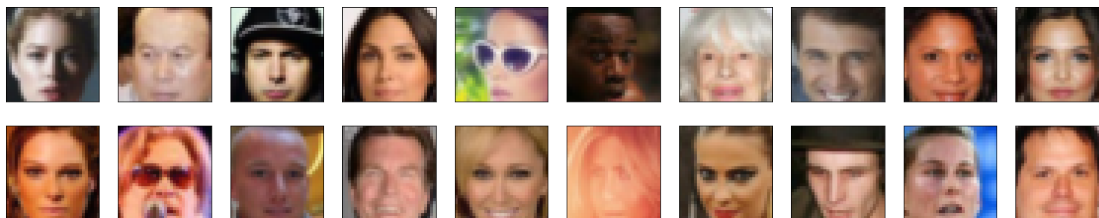
In [6]: # helper display function
        def imshow(img):
            npimg = img.numpy()
            plt.imshow(np.transpose(npimg, (1, 2, 0)))

            """
            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 [7]: # 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 [8]: """
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(-0.8353)
```

```
Max:  tensor(0.9059)
```

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

2.2 Helper Function

```
In [10]: # 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 [11]: 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)

        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 [12]: `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 [13]: 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 [14]: """
        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 [15]: # 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 [16]: """
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 [17]: 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 [18]: import torch.optim as optim

d_optimizer = optim.Adam(D.parameters(), lr=0.001, betas=(0.5, 0.999))
g_optimizer = optim.Adam(G.parameters(), lr=0.001, betas=(0.5, 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 [19]: 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 [20]: # set number of epochs
         n_epochs = 20

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

         # call training function
         losses = train(D, G, n_epochs=n_epochs)

Epoch [ 1/ 20] | d_loss: 1.3410 | g_loss: 1.6877
Epoch [ 1/ 20] | d_loss: 0.8083 | g_loss: 2.5227
Epoch [ 1/ 20] | d_loss: 0.9431 | g_loss: 2.5018
Epoch [ 1/ 20] | d_loss: 1.2149 | g_loss: 3.4194
Epoch [ 1/ 20] | d_loss: 1.7443 | g_loss: 3.0724
Epoch [ 1/ 20] | d_loss: 1.7218 | g_loss: 0.7178
Epoch [ 1/ 20] | d_loss: 0.9594 | g_loss: 2.7744
Epoch [ 1/ 20] | d_loss: 1.3631 | g_loss: 1.2735
Epoch [ 1/ 20] | d_loss: 1.0233 | g_loss: 1.3976
Epoch [ 1/ 20] | d_loss: 2.0550 | g_loss: 2.2664
Epoch [ 1/ 20] | d_loss: 1.1259 | g_loss: 2.2083
Epoch [ 1/ 20] | d_loss: 0.8518 | g_loss: 2.5673
Epoch [ 1/ 20] | d_loss: 0.8047 | g_loss: 2.6363
Epoch [ 1/ 20] | d_loss: 1.0739 | g_loss: 1.6434
Epoch [ 1/ 20] | d_loss: 0.9607 | g_loss: 2.1572
Epoch [ 1/ 20] | d_loss: 0.9879 | g_loss: 3.8284
Epoch [ 1/ 20] | d_loss: 0.9688 | g_loss: 4.0602
Epoch [ 1/ 20] | d_loss: 0.8698 | g_loss: 2.1034
Epoch [ 1/ 20] | d_loss: 0.9104 | g_loss: 1.5537
Epoch [ 1/ 20] | d_loss: 1.3113 | g_loss: 3.6388
Epoch [ 1/ 20] | d_loss: 1.7428 | g_loss: 1.4453

```

Epoch [1/	20]	d_loss: 1.1188	g_loss: 2.3361
Epoch [1/	20]	d_loss: 0.9638	g_loss: 1.8358
Epoch [1/	20]	d_loss: 1.2751	g_loss: 1.7968
Epoch [1/	20]	d_loss: 0.9835	g_loss: 1.3598
Epoch [1/	20]	d_loss: 1.0427	g_loss: 1.8447
Epoch [1/	20]	d_loss: 1.0476	g_loss: 1.8864
Epoch [1/	20]	d_loss: 0.9795	g_loss: 1.7668
Epoch [1/	20]	d_loss: 0.8867	g_loss: 2.1969
Epoch [1/	20]	d_loss: 0.8768	g_loss: 1.6812
Epoch [1/	20]	d_loss: 0.9383	g_loss: 2.2353
Epoch [1/	20]	d_loss: 0.7446	g_loss: 2.2385
Epoch [1/	20]	d_loss: 0.7735	g_loss: 1.6826
Epoch [1/	20]	d_loss: 1.3513	g_loss: 3.3663
Epoch [1/	20]	d_loss: 1.0557	g_loss: 1.9687
Epoch [1/	20]	d_loss: 0.8460	g_loss: 2.1474
Epoch [1/	20]	d_loss: 1.2995	g_loss: 3.0650
Epoch [1/	20]	d_loss: 1.1965	g_loss: 0.9526
Epoch [1/	20]	d_loss: 1.1108	g_loss: 1.3406
Epoch [1/	20]	d_loss: 0.7843	g_loss: 2.7248
Epoch [1/	20]	d_loss: 1.0116	g_loss: 1.8359
Epoch [1/	20]	d_loss: 1.1895	g_loss: 1.8590
Epoch [1/	20]	d_loss: 0.9884	g_loss: 2.6506
Epoch [1/	20]	d_loss: 1.2924	g_loss: 3.6007
Epoch [1/	20]	d_loss: 0.7762	g_loss: 2.1436
Epoch [1/	20]	d_loss: 0.9187	g_loss: 1.8038
Epoch [1/	20]	d_loss: 0.8312	g_loss: 2.0580
Epoch [1/	20]	d_loss: 1.0605	g_loss: 1.8067
Epoch [1/	20]	d_loss: 1.0432	g_loss: 2.5434
Epoch [1/	20]	d_loss: 0.9691	g_loss: 2.4716
Epoch [1/	20]	d_loss: 0.9586	g_loss: 1.9098
Epoch [1/	20]	d_loss: 0.9474	g_loss: 1.3652
Epoch [1/	20]	d_loss: 0.7870	g_loss: 1.7143
Epoch [1/	20]	d_loss: 1.1287	g_loss: 2.3689
Epoch [1/	20]	d_loss: 1.1794	g_loss: 1.5965
Epoch [1/	20]	d_loss: 0.7117	g_loss: 2.3417
Epoch [1/	20]	d_loss: 1.2059	g_loss: 1.4837
Epoch [2/	20]	d_loss: 0.9094	g_loss: 1.6220
Epoch [2/	20]	d_loss: 0.9585	g_loss: 1.7712
Epoch [2/	20]	d_loss: 0.8404	g_loss: 2.2448
Epoch [2/	20]	d_loss: 1.0190	g_loss: 1.7595
Epoch [2/	20]	d_loss: 0.9950	g_loss: 1.5382
Epoch [2/	20]	d_loss: 1.0275	g_loss: 1.6162
Epoch [2/	20]	d_loss: 0.9559	g_loss: 2.4432
Epoch [2/	20]	d_loss: 0.8937	g_loss: 2.3655
Epoch [2/	20]	d_loss: 0.9548	g_loss: 1.4474
Epoch [2/	20]	d_loss: 1.1028	g_loss: 1.9325
Epoch [2/	20]	d_loss: 1.1137	g_loss: 1.8271
Epoch [2/	20]	d_loss: 0.8954	g_loss: 2.2566

Epoch [2/	20]	d_loss: 1.0349	g_loss: 1.4165
Epoch [2/	20]	d_loss: 0.9451	g_loss: 1.4964
Epoch [2/	20]	d_loss: 0.9680	g_loss: 1.9507
Epoch [2/	20]	d_loss: 0.9172	g_loss: 2.5064
Epoch [2/	20]	d_loss: 0.8907	g_loss: 1.6503
Epoch [2/	20]	d_loss: 1.1239	g_loss: 2.3504
Epoch [2/	20]	d_loss: 1.1258	g_loss: 1.0853
Epoch [2/	20]	d_loss: 0.8395	g_loss: 2.0416
Epoch [2/	20]	d_loss: 1.0543	g_loss: 2.0583
Epoch [2/	20]	d_loss: 1.4673	g_loss: 1.8123
Epoch [2/	20]	d_loss: 1.4406	g_loss: 1.3683
Epoch [2/	20]	d_loss: 1.1991	g_loss: 1.5417
Epoch [2/	20]	d_loss: 1.0116	g_loss: 1.5197
Epoch [2/	20]	d_loss: 1.2217	g_loss: 1.8361
Epoch [2/	20]	d_loss: 1.3713	g_loss: 2.1051
Epoch [2/	20]	d_loss: 1.2523	g_loss: 2.1729
Epoch [2/	20]	d_loss: 1.1620	g_loss: 0.9532
Epoch [2/	20]	d_loss: 1.3034	g_loss: 1.3336
Epoch [2/	20]	d_loss: 1.0637	g_loss: 1.0934
Epoch [2/	20]	d_loss: 1.1131	g_loss: 0.6317
Epoch [2/	20]	d_loss: 1.1693	g_loss: 2.2442
Epoch [2/	20]	d_loss: 0.9729	g_loss: 2.0116
Epoch [2/	20]	d_loss: 0.8379	g_loss: 1.7079
Epoch [2/	20]	d_loss: 1.0573	g_loss: 1.7950
Epoch [2/	20]	d_loss: 1.0828	g_loss: 1.6619
Epoch [2/	20]	d_loss: 0.9721	g_loss: 1.4295
Epoch [2/	20]	d_loss: 0.9534	g_loss: 2.2124
Epoch [2/	20]	d_loss: 1.1340	g_loss: 1.7049
Epoch [2/	20]	d_loss: 1.1888	g_loss: 2.0104
Epoch [2/	20]	d_loss: 0.9348	g_loss: 1.8717
Epoch [2/	20]	d_loss: 1.0892	g_loss: 1.2627
Epoch [2/	20]	d_loss: 1.2123	g_loss: 2.3151
Epoch [2/	20]	d_loss: 1.0010	g_loss: 1.3907
Epoch [2/	20]	d_loss: 1.0612	g_loss: 2.5985
Epoch [2/	20]	d_loss: 1.1025	g_loss: 1.4520
Epoch [2/	20]	d_loss: 0.8838	g_loss: 1.9847
Epoch [2/	20]	d_loss: 0.9856	g_loss: 1.2092
Epoch [2/	20]	d_loss: 0.8597	g_loss: 2.1875
Epoch [2/	20]	d_loss: 1.1347	g_loss: 1.8924
Epoch [2/	20]	d_loss: 1.5894	g_loss: 0.7019
Epoch [2/	20]	d_loss: 0.9852	g_loss: 1.0994
Epoch [2/	20]	d_loss: 1.1059	g_loss: 1.7722
Epoch [2/	20]	d_loss: 0.9116	g_loss: 1.5727
Epoch [2/	20]	d_loss: 1.3994	g_loss: 1.3781
Epoch [2/	20]	d_loss: 1.1416	g_loss: 1.3420
Epoch [3/	20]	d_loss: 1.3941	g_loss: 2.6468
Epoch [3/	20]	d_loss: 1.2275	g_loss: 1.0323
Epoch [3/	20]	d_loss: 0.9345	g_loss: 2.0826

Epoch [3/	20]	d_loss: 0.9573	g_loss: 1.9348
Epoch [3/	20]	d_loss: 1.0714	g_loss: 1.5194
Epoch [3/	20]	d_loss: 1.3877	g_loss: 2.2767
Epoch [3/	20]	d_loss: 1.1236	g_loss: 1.8957
Epoch [3/	20]	d_loss: 1.0790	g_loss: 0.8222
Epoch [3/	20]	d_loss: 0.9682	g_loss: 1.4873
Epoch [3/	20]	d_loss: 1.0002	g_loss: 1.5789
Epoch [3/	20]	d_loss: 0.9438	g_loss: 1.4569
Epoch [3/	20]	d_loss: 1.6300	g_loss: 1.2499
Epoch [3/	20]	d_loss: 0.9431	g_loss: 0.9553
Epoch [3/	20]	d_loss: 1.0703	g_loss: 2.4924
Epoch [3/	20]	d_loss: 0.9501	g_loss: 1.8735
Epoch [3/	20]	d_loss: 1.1096	g_loss: 1.5766
Epoch [3/	20]	d_loss: 1.3704	g_loss: 1.9476
Epoch [3/	20]	d_loss: 1.1882	g_loss: 2.4412
Epoch [3/	20]	d_loss: 1.0843	g_loss: 1.1336
Epoch [3/	20]	d_loss: 0.9643	g_loss: 2.2593
Epoch [3/	20]	d_loss: 0.8856	g_loss: 1.8746
Epoch [3/	20]	d_loss: 1.1749	g_loss: 1.4251
Epoch [3/	20]	d_loss: 1.0128	g_loss: 2.2875
Epoch [3/	20]	d_loss: 1.4404	g_loss: 1.2730
Epoch [3/	20]	d_loss: 0.9387	g_loss: 1.3545
Epoch [3/	20]	d_loss: 1.1194	g_loss: 1.6593
Epoch [3/	20]	d_loss: 1.2043	g_loss: 1.2151
Epoch [3/	20]	d_loss: 1.1007	g_loss: 1.7584
Epoch [3/	20]	d_loss: 1.1406	g_loss: 1.4594
Epoch [3/	20]	d_loss: 0.8827	g_loss: 1.1260
Epoch [3/	20]	d_loss: 0.8915	g_loss: 1.5009
Epoch [3/	20]	d_loss: 1.2010	g_loss: 1.1046
Epoch [3/	20]	d_loss: 1.0124	g_loss: 1.8946
Epoch [3/	20]	d_loss: 0.8624	g_loss: 1.5483
Epoch [3/	20]	d_loss: 1.1528	g_loss: 2.2400
Epoch [3/	20]	d_loss: 1.0025	g_loss: 1.3095
Epoch [3/	20]	d_loss: 1.0074	g_loss: 1.8313
Epoch [3/	20]	d_loss: 1.0708	g_loss: 2.3802
Epoch [3/	20]	d_loss: 1.1420	g_loss: 1.3077
Epoch [3/	20]	d_loss: 1.1235	g_loss: 1.0105
Epoch [3/	20]	d_loss: 1.1003	g_loss: 1.8940
Epoch [3/	20]	d_loss: 1.2442	g_loss: 1.7590
Epoch [3/	20]	d_loss: 1.0573	g_loss: 1.5636
Epoch [3/	20]	d_loss: 1.4217	g_loss: 1.3573
Epoch [3/	20]	d_loss: 0.9569	g_loss: 1.9019
Epoch [3/	20]	d_loss: 1.0048	g_loss: 1.9369
Epoch [3/	20]	d_loss: 1.3304	g_loss: 1.5377
Epoch [3/	20]	d_loss: 1.3715	g_loss: 1.4302
Epoch [3/	20]	d_loss: 1.0975	g_loss: 1.6516
Epoch [3/	20]	d_loss: 1.2265	g_loss: 1.2618
Epoch [3/	20]	d_loss: 1.0727	g_loss: 1.6169

Epoch [3/	20]	d_loss: 1.0492	g_loss: 1.6460
Epoch [3/	20]	d_loss: 1.0186	g_loss: 1.3522
Epoch [3/	20]	d_loss: 1.3181	g_loss: 1.5211
Epoch [3/	20]	d_loss: 0.9494	g_loss: 1.6803
Epoch [3/	20]	d_loss: 0.9418	g_loss: 2.0692
Epoch [3/	20]	d_loss: 0.8340	g_loss: 1.5124
Epoch [4/	20]	d_loss: 1.5142	g_loss: 0.8316
Epoch [4/	20]	d_loss: 1.1340	g_loss: 1.8879
Epoch [4/	20]	d_loss: 0.9550	g_loss: 1.1428
Epoch [4/	20]	d_loss: 0.8376	g_loss: 1.9751
Epoch [4/	20]	d_loss: 0.8636	g_loss: 2.2758
Epoch [4/	20]	d_loss: 1.0789	g_loss: 2.1645
Epoch [4/	20]	d_loss: 0.9338	g_loss: 1.3286
Epoch [4/	20]	d_loss: 1.0616	g_loss: 0.9878
Epoch [4/	20]	d_loss: 1.0665	g_loss: 0.9668
Epoch [4/	20]	d_loss: 0.9935	g_loss: 1.9654
Epoch [4/	20]	d_loss: 0.9366	g_loss: 1.1873
Epoch [4/	20]	d_loss: 0.8429	g_loss: 2.1554
Epoch [4/	20]	d_loss: 0.8265	g_loss: 1.2704
Epoch [4/	20]	d_loss: 1.1360	g_loss: 2.0538
Epoch [4/	20]	d_loss: 1.0645	g_loss: 1.6111
Epoch [4/	20]	d_loss: 1.0714	g_loss: 1.7898
Epoch [4/	20]	d_loss: 1.1571	g_loss: 1.6686
Epoch [4/	20]	d_loss: 1.3667	g_loss: 1.1974
Epoch [4/	20]	d_loss: 1.2227	g_loss: 1.9541
Epoch [4/	20]	d_loss: 1.4113	g_loss: 1.3141
Epoch [4/	20]	d_loss: 0.8956	g_loss: 1.6508
Epoch [4/	20]	d_loss: 1.0139	g_loss: 2.0187
Epoch [4/	20]	d_loss: 1.1382	g_loss: 1.3817
Epoch [4/	20]	d_loss: 1.0314	g_loss: 1.1840
Epoch [4/	20]	d_loss: 0.8524	g_loss: 2.0104
Epoch [4/	20]	d_loss: 1.2173	g_loss: 1.1716
Epoch [4/	20]	d_loss: 1.1469	g_loss: 1.4327
Epoch [4/	20]	d_loss: 1.1670	g_loss: 1.5926
Epoch [4/	20]	d_loss: 1.0451	g_loss: 2.2475
Epoch [4/	20]	d_loss: 0.9615	g_loss: 1.6077
Epoch [4/	20]	d_loss: 0.9233	g_loss: 1.5778
Epoch [4/	20]	d_loss: 0.6748	g_loss: 1.9946
Epoch [4/	20]	d_loss: 1.1497	g_loss: 2.0976
Epoch [4/	20]	d_loss: 1.1940	g_loss: 2.2202
Epoch [4/	20]	d_loss: 1.1119	g_loss: 1.7764
Epoch [4/	20]	d_loss: 0.9704	g_loss: 1.9333
Epoch [4/	20]	d_loss: 1.1646	g_loss: 2.1435
Epoch [4/	20]	d_loss: 1.0567	g_loss: 1.1359
Epoch [4/	20]	d_loss: 0.9990	g_loss: 1.1512
Epoch [4/	20]	d_loss: 1.0960	g_loss: 1.8922
Epoch [4/	20]	d_loss: 0.6894	g_loss: 2.2372
Epoch [4/	20]	d_loss: 1.0886	g_loss: 1.1624

Epoch [4/	20]	d_loss: 1.0955	g_loss: 1.5626
Epoch [4/	20]	d_loss: 1.0434	g_loss: 1.0882
Epoch [4/	20]	d_loss: 0.8885	g_loss: 1.6196
Epoch [4/	20]	d_loss: 1.1111	g_loss: 0.9941
Epoch [4/	20]	d_loss: 1.3397	g_loss: 1.1548
Epoch [4/	20]	d_loss: 0.8940	g_loss: 1.4756
Epoch [4/	20]	d_loss: 1.1399	g_loss: 1.3099
Epoch [4/	20]	d_loss: 1.0765	g_loss: 1.7075
Epoch [4/	20]	d_loss: 1.0793	g_loss: 1.7735
Epoch [4/	20]	d_loss: 1.0666	g_loss: 2.1943
Epoch [4/	20]	d_loss: 0.6747	g_loss: 2.4924
Epoch [4/	20]	d_loss: 1.1243	g_loss: 1.1790
Epoch [4/	20]	d_loss: 1.0284	g_loss: 2.1970
Epoch [4/	20]	d_loss: 1.0078	g_loss: 1.3991
Epoch [4/	20]	d_loss: 1.7040	g_loss: 1.9945
Epoch [5/	20]	d_loss: 0.8901	g_loss: 2.4324
Epoch [5/	20]	d_loss: 0.8928	g_loss: 1.3646
Epoch [5/	20]	d_loss: 0.9072	g_loss: 2.3640
Epoch [5/	20]	d_loss: 1.0055	g_loss: 2.4067
Epoch [5/	20]	d_loss: 0.8902	g_loss: 1.3025
Epoch [5/	20]	d_loss: 1.0305	g_loss: 1.2618
Epoch [5/	20]	d_loss: 1.0351	g_loss: 2.2770
Epoch [5/	20]	d_loss: 0.6919	g_loss: 2.2477
Epoch [5/	20]	d_loss: 0.9383	g_loss: 2.7969
Epoch [5/	20]	d_loss: 1.0097	g_loss: 0.9729
Epoch [5/	20]	d_loss: 0.9176	g_loss: 1.8666
Epoch [5/	20]	d_loss: 0.8321	g_loss: 1.5919
Epoch [5/	20]	d_loss: 1.1407	g_loss: 0.8511
Epoch [5/	20]	d_loss: 0.9464	g_loss: 1.9345
Epoch [5/	20]	d_loss: 0.8874	g_loss: 1.7828
Epoch [5/	20]	d_loss: 1.0889	g_loss: 1.5045
Epoch [5/	20]	d_loss: 1.1125	g_loss: 1.7017
Epoch [5/	20]	d_loss: 0.8589	g_loss: 1.9159
Epoch [5/	20]	d_loss: 1.1825	g_loss: 1.8010
Epoch [5/	20]	d_loss: 0.9907	g_loss: 2.0119
Epoch [5/	20]	d_loss: 1.0713	g_loss: 1.1380
Epoch [5/	20]	d_loss: 0.9846	g_loss: 1.4710
Epoch [5/	20]	d_loss: 0.9546	g_loss: 2.1470
Epoch [5/	20]	d_loss: 0.9612	g_loss: 1.6308
Epoch [5/	20]	d_loss: 1.2216	g_loss: 1.3448
Epoch [5/	20]	d_loss: 0.8024	g_loss: 1.7310
Epoch [5/	20]	d_loss: 0.9915	g_loss: 1.7016
Epoch [5/	20]	d_loss: 1.1087	g_loss: 0.8234
Epoch [5/	20]	d_loss: 1.0075	g_loss: 2.0422
Epoch [5/	20]	d_loss: 1.0165	g_loss: 1.0873
Epoch [5/	20]	d_loss: 1.0095	g_loss: 1.4464
Epoch [5/	20]	d_loss: 1.2327	g_loss: 1.0699
Epoch [5/	20]	d_loss: 0.9813	g_loss: 1.5446

Epoch [5/	20]	d_loss: 1.0009	g_loss: 1.2067
Epoch [5/	20]	d_loss: 1.0737	g_loss: 1.9417
Epoch [5/	20]	d_loss: 1.3185	g_loss: 2.1866
Epoch [5/	20]	d_loss: 0.9853	g_loss: 1.0789
Epoch [5/	20]	d_loss: 0.9530	g_loss: 1.7885
Epoch [5/	20]	d_loss: 0.9326	g_loss: 2.0430
Epoch [5/	20]	d_loss: 0.8851	g_loss: 1.2641
Epoch [5/	20]	d_loss: 0.9381	g_loss: 0.8336
Epoch [5/	20]	d_loss: 0.6952	g_loss: 1.5381
Epoch [5/	20]	d_loss: 1.3295	g_loss: 2.0059
Epoch [5/	20]	d_loss: 0.6894	g_loss: 2.4495
Epoch [5/	20]	d_loss: 0.9533	g_loss: 1.6122
Epoch [5/	20]	d_loss: 0.8554	g_loss: 1.8900
Epoch [5/	20]	d_loss: 1.1598	g_loss: 1.0663
Epoch [5/	20]	d_loss: 0.8030	g_loss: 1.9633
Epoch [5/	20]	d_loss: 1.0294	g_loss: 0.9226
Epoch [5/	20]	d_loss: 0.7200	g_loss: 1.0300
Epoch [5/	20]	d_loss: 1.1315	g_loss: 1.7883
Epoch [5/	20]	d_loss: 1.0711	g_loss: 1.5376
Epoch [5/	20]	d_loss: 0.9525	g_loss: 1.3630
Epoch [5/	20]	d_loss: 1.1085	g_loss: 1.7579
Epoch [5/	20]	d_loss: 0.9633	g_loss: 1.7216
Epoch [5/	20]	d_loss: 1.1091	g_loss: 1.7189
Epoch [5/	20]	d_loss: 0.9220	g_loss: 1.5813
Epoch [6/	20]	d_loss: 1.0488	g_loss: 1.6270
Epoch [6/	20]	d_loss: 0.9536	g_loss: 1.6653
Epoch [6/	20]	d_loss: 1.0810	g_loss: 1.1424
Epoch [6/	20]	d_loss: 1.2529	g_loss: 1.1532
Epoch [6/	20]	d_loss: 0.9694	g_loss: 1.7206
Epoch [6/	20]	d_loss: 0.9474	g_loss: 1.3738
Epoch [6/	20]	d_loss: 1.2262	g_loss: 1.9109
Epoch [6/	20]	d_loss: 0.7310	g_loss: 2.4873
Epoch [6/	20]	d_loss: 0.9578	g_loss: 1.4205
Epoch [6/	20]	d_loss: 0.8391	g_loss: 2.1003
Epoch [6/	20]	d_loss: 1.5452	g_loss: 1.5038
Epoch [6/	20]	d_loss: 2.3877	g_loss: 2.6137
Epoch [6/	20]	d_loss: 1.4421	g_loss: 2.7658
Epoch [6/	20]	d_loss: 0.7360	g_loss: 1.6568
Epoch [6/	20]	d_loss: 1.3938	g_loss: 1.3446
Epoch [6/	20]	d_loss: 2.1651	g_loss: 1.6014
Epoch [6/	20]	d_loss: 0.8241	g_loss: 1.6208
Epoch [6/	20]	d_loss: 0.6933	g_loss: 2.1155
Epoch [6/	20]	d_loss: 0.9140	g_loss: 1.8002
Epoch [6/	20]	d_loss: 1.1477	g_loss: 1.6900
Epoch [6/	20]	d_loss: 0.6583	g_loss: 1.5776
Epoch [6/	20]	d_loss: 0.8411	g_loss: 1.0656
Epoch [6/	20]	d_loss: 0.9438	g_loss: 2.5059
Epoch [6/	20]	d_loss: 1.2612	g_loss: 1.1200

Epoch [6/	20]	d_loss: 0.8428	g_loss: 2.2863
Epoch [6/	20]	d_loss: 0.7016	g_loss: 2.8809
Epoch [6/	20]	d_loss: 1.1341	g_loss: 1.7779
Epoch [6/	20]	d_loss: 1.0307	g_loss: 1.5960
Epoch [6/	20]	d_loss: 1.1288	g_loss: 2.4794
Epoch [6/	20]	d_loss: 1.2157	g_loss: 2.9539
Epoch [6/	20]	d_loss: 0.7961	g_loss: 1.5473
Epoch [6/	20]	d_loss: 0.7690	g_loss: 1.9322
Epoch [6/	20]	d_loss: 0.6972	g_loss: 1.0251
Epoch [6/	20]	d_loss: 1.3472	g_loss: 1.3406
Epoch [6/	20]	d_loss: 0.8131	g_loss: 1.7482
Epoch [6/	20]	d_loss: 1.0422	g_loss: 1.4427
Epoch [6/	20]	d_loss: 0.8503	g_loss: 2.6571
Epoch [6/	20]	d_loss: 1.0755	g_loss: 2.7085
Epoch [6/	20]	d_loss: 0.5543	g_loss: 1.1587
Epoch [6/	20]	d_loss: 1.3317	g_loss: 1.4151
Epoch [6/	20]	d_loss: 0.7668	g_loss: 1.1039
Epoch [6/	20]	d_loss: 1.0458	g_loss: 1.5796
Epoch [6/	20]	d_loss: 1.1503	g_loss: 1.6051
Epoch [6/	20]	d_loss: 0.9501	g_loss: 1.3939
Epoch [6/	20]	d_loss: 0.7846	g_loss: 1.3245
Epoch [6/	20]	d_loss: 0.8688	g_loss: 2.2101
Epoch [6/	20]	d_loss: 1.0552	g_loss: 1.3938
Epoch [6/	20]	d_loss: 1.1809	g_loss: 1.1041
Epoch [6/	20]	d_loss: 1.0089	g_loss: 1.2802
Epoch [6/	20]	d_loss: 1.0149	g_loss: 1.7091
Epoch [6/	20]	d_loss: 1.1441	g_loss: 2.2536
Epoch [6/	20]	d_loss: 0.6962	g_loss: 1.9467
Epoch [6/	20]	d_loss: 1.0782	g_loss: 1.3300
Epoch [6/	20]	d_loss: 0.8918	g_loss: 1.4299
Epoch [6/	20]	d_loss: 0.8211	g_loss: 2.1342
Epoch [6/	20]	d_loss: 1.2838	g_loss: 1.9691
Epoch [6/	20]	d_loss: 1.1194	g_loss: 1.8925
Epoch [7/	20]	d_loss: 0.8074	g_loss: 1.2777
Epoch [7/	20]	d_loss: 1.0993	g_loss: 1.5489
Epoch [7/	20]	d_loss: 0.8602	g_loss: 2.4790
Epoch [7/	20]	d_loss: 0.9960	g_loss: 2.0519
Epoch [7/	20]	d_loss: 1.4975	g_loss: 1.8272
Epoch [7/	20]	d_loss: 0.7493	g_loss: 2.1340
Epoch [7/	20]	d_loss: 0.8407	g_loss: 2.2850
Epoch [7/	20]	d_loss: 1.0513	g_loss: 1.6050
Epoch [7/	20]	d_loss: 0.7857	g_loss: 2.0806
Epoch [7/	20]	d_loss: 0.9778	g_loss: 2.3099
Epoch [7/	20]	d_loss: 0.9993	g_loss: 2.7715
Epoch [7/	20]	d_loss: 1.0938	g_loss: 1.4697
Epoch [7/	20]	d_loss: 0.8482	g_loss: 2.3677
Epoch [7/	20]	d_loss: 1.2949	g_loss: 1.4811
Epoch [7/	20]	d_loss: 1.1720	g_loss: 1.7462

Epoch [7/	20]	d_loss: 0.9126	g_loss: 2.0487
Epoch [7/	20]	d_loss: 1.0603	g_loss: 1.6304
Epoch [7/	20]	d_loss: 0.7708	g_loss: 1.7864
Epoch [7/	20]	d_loss: 1.0079	g_loss: 1.8211
Epoch [7/	20]	d_loss: 1.6345	g_loss: 1.7260
Epoch [7/	20]	d_loss: 0.8616	g_loss: 2.8633
Epoch [7/	20]	d_loss: 0.7943	g_loss: 1.8359
Epoch [7/	20]	d_loss: 0.9330	g_loss: 2.0738
Epoch [7/	20]	d_loss: 1.0051	g_loss: 2.7588
Epoch [7/	20]	d_loss: 0.8659	g_loss: 1.8570
Epoch [7/	20]	d_loss: 0.7483	g_loss: 1.1572
Epoch [7/	20]	d_loss: 0.8856	g_loss: 1.8228
Epoch [7/	20]	d_loss: 1.4415	g_loss: 2.2207
Epoch [7/	20]	d_loss: 0.7432	g_loss: 2.5737
Epoch [7/	20]	d_loss: 0.8467	g_loss: 2.0599
Epoch [7/	20]	d_loss: 1.1409	g_loss: 0.7903
Epoch [7/	20]	d_loss: 0.6581	g_loss: 2.7223
Epoch [7/	20]	d_loss: 0.6663	g_loss: 2.4738
Epoch [7/	20]	d_loss: 1.2880	g_loss: 1.2204
Epoch [7/	20]	d_loss: 1.1043	g_loss: 1.5499
Epoch [7/	20]	d_loss: 0.7580	g_loss: 1.6071
Epoch [7/	20]	d_loss: 0.7739	g_loss: 1.0236
Epoch [7/	20]	d_loss: 0.9728	g_loss: 3.0191
Epoch [7/	20]	d_loss: 0.7476	g_loss: 2.4810
Epoch [7/	20]	d_loss: 0.8540	g_loss: 1.1241
Epoch [7/	20]	d_loss: 0.8661	g_loss: 2.0064
Epoch [7/	20]	d_loss: 0.7292	g_loss: 1.3680
Epoch [7/	20]	d_loss: 0.7976	g_loss: 1.5648
Epoch [7/	20]	d_loss: 1.0501	g_loss: 1.1225
Epoch [7/	20]	d_loss: 1.0486	g_loss: 1.9106
Epoch [7/	20]	d_loss: 0.9805	g_loss: 1.7900
Epoch [7/	20]	d_loss: 0.8760	g_loss: 2.0870
Epoch [7/	20]	d_loss: 0.7017	g_loss: 1.5833
Epoch [7/	20]	d_loss: 0.6658	g_loss: 2.2209
Epoch [7/	20]	d_loss: 0.9134	g_loss: 2.1912
Epoch [7/	20]	d_loss: 1.4476	g_loss: 2.7825
Epoch [7/	20]	d_loss: 0.8492	g_loss: 1.7715
Epoch [7/	20]	d_loss: 0.8927	g_loss: 3.1184
Epoch [7/	20]	d_loss: 0.5832	g_loss: 1.9596
Epoch [7/	20]	d_loss: 0.9458	g_loss: 1.6788
Epoch [7/	20]	d_loss: 0.8262	g_loss: 3.6936
Epoch [7/	20]	d_loss: 0.9384	g_loss: 1.5279
Epoch [8/	20]	d_loss: 1.2418	g_loss: 1.1173
Epoch [8/	20]	d_loss: 0.7253	g_loss: 2.0997
Epoch [8/	20]	d_loss: 1.1337	g_loss: 1.5788
Epoch [8/	20]	d_loss: 0.9958	g_loss: 1.5526
Epoch [8/	20]	d_loss: 1.0806	g_loss: 2.5134
Epoch [8/	20]	d_loss: 1.0343	g_loss: 1.9920

Epoch [8/	20]	d_loss: 0.7750	g_loss: 1.1636
Epoch [8/	20]	d_loss: 1.0802	g_loss: 2.3683
Epoch [8/	20]	d_loss: 1.0549	g_loss: 2.2435
Epoch [8/	20]	d_loss: 1.6158	g_loss: 1.6031
Epoch [8/	20]	d_loss: 0.7114	g_loss: 2.2871
Epoch [8/	20]	d_loss: 0.9751	g_loss: 1.9100
Epoch [8/	20]	d_loss: 0.6140	g_loss: 2.1776
Epoch [8/	20]	d_loss: 0.9664	g_loss: 1.5029
Epoch [8/	20]	d_loss: 0.6933	g_loss: 3.1789
Epoch [8/	20]	d_loss: 1.1110	g_loss: 1.4896
Epoch [8/	20]	d_loss: 0.9496	g_loss: 1.5429
Epoch [8/	20]	d_loss: 0.7460	g_loss: 1.4061
Epoch [8/	20]	d_loss: 1.0271	g_loss: 1.7233
Epoch [8/	20]	d_loss: 1.1428	g_loss: 1.1510
Epoch [8/	20]	d_loss: 1.4805	g_loss: 1.9683
Epoch [8/	20]	d_loss: 2.0902	g_loss: 1.0955
Epoch [8/	20]	d_loss: 0.8361	g_loss: 1.1694
Epoch [8/	20]	d_loss: 1.5236	g_loss: 1.5805
Epoch [8/	20]	d_loss: 0.7032	g_loss: 1.2869
Epoch [8/	20]	d_loss: 0.8642	g_loss: 1.8553
Epoch [8/	20]	d_loss: 0.8421	g_loss: 1.2544
Epoch [8/	20]	d_loss: 0.6808	g_loss: 1.9333
Epoch [8/	20]	d_loss: 0.9138	g_loss: 0.7444
Epoch [8/	20]	d_loss: 0.8290	g_loss: 3.2469
Epoch [8/	20]	d_loss: 1.1009	g_loss: 1.3451
Epoch [8/	20]	d_loss: 0.5889	g_loss: 1.7209
Epoch [8/	20]	d_loss: 0.9868	g_loss: 2.7003
Epoch [8/	20]	d_loss: 0.6479	g_loss: 1.2738
Epoch [8/	20]	d_loss: 0.7370	g_loss: 2.4645
Epoch [8/	20]	d_loss: 1.5040	g_loss: 2.0487
Epoch [8/	20]	d_loss: 1.0662	g_loss: 1.2676
Epoch [8/	20]	d_loss: 0.9688	g_loss: 1.9704
Epoch [8/	20]	d_loss: 1.3498	g_loss: 0.9855
Epoch [8/	20]	d_loss: 1.5557	g_loss: 0.7540
Epoch [8/	20]	d_loss: 1.1011	g_loss: 1.2944
Epoch [8/	20]	d_loss: 0.7999	g_loss: 1.4615
Epoch [8/	20]	d_loss: 0.8555	g_loss: 1.2924
Epoch [8/	20]	d_loss: 1.0586	g_loss: 1.6241
Epoch [8/	20]	d_loss: 1.4615	g_loss: 1.9980
Epoch [8/	20]	d_loss: 1.2141	g_loss: 1.4996
Epoch [8/	20]	d_loss: 0.6511	g_loss: 1.9302
Epoch [8/	20]	d_loss: 0.6358	g_loss: 2.7789
Epoch [8/	20]	d_loss: 0.9147	g_loss: 2.1776
Epoch [8/	20]	d_loss: 0.9098	g_loss: 0.5851
Epoch [8/	20]	d_loss: 1.2212	g_loss: 2.6697
Epoch [8/	20]	d_loss: 1.0504	g_loss: 2.2149
Epoch [8/	20]	d_loss: 0.7319	g_loss: 1.5682
Epoch [8/	20]	d_loss: 1.0562	g_loss: 0.7793

Epoch [8/	20]	d_loss: 1.1532	g_loss: 2.3951
Epoch [8/	20]	d_loss: 0.8775	g_loss: 1.8595
Epoch [8/	20]	d_loss: 1.2122	g_loss: 1.5395
Epoch [9/	20]	d_loss: 1.3657	g_loss: 1.3099
Epoch [9/	20]	d_loss: 0.5584	g_loss: 3.1783
Epoch [9/	20]	d_loss: 0.6522	g_loss: 2.5068
Epoch [9/	20]	d_loss: 1.0440	g_loss: 1.9683
Epoch [9/	20]	d_loss: 0.8096	g_loss: 1.8878
Epoch [9/	20]	d_loss: 0.8019	g_loss: 2.2206
Epoch [9/	20]	d_loss: 0.7028	g_loss: 2.2059
Epoch [9/	20]	d_loss: 1.0821	g_loss: 2.4425
Epoch [9/	20]	d_loss: 0.5671	g_loss: 2.4308
Epoch [9/	20]	d_loss: 0.5541	g_loss: 2.9056
Epoch [9/	20]	d_loss: 0.7006	g_loss: 1.9342
Epoch [9/	20]	d_loss: 0.6915	g_loss: 2.1988
Epoch [9/	20]	d_loss: 0.6361	g_loss: 2.0149
Epoch [9/	20]	d_loss: 1.1282	g_loss: 1.3757
Epoch [9/	20]	d_loss: 0.6713	g_loss: 2.4115
Epoch [9/	20]	d_loss: 0.9905	g_loss: 1.6673
Epoch [9/	20]	d_loss: 0.7543	g_loss: 2.6038
Epoch [9/	20]	d_loss: 0.8552	g_loss: 2.0164
Epoch [9/	20]	d_loss: 0.7924	g_loss: 2.8267
Epoch [9/	20]	d_loss: 0.8261	g_loss: 2.2491
Epoch [9/	20]	d_loss: 0.8304	g_loss: 1.5020
Epoch [9/	20]	d_loss: 0.7095	g_loss: 1.9923
Epoch [9/	20]	d_loss: 1.4415	g_loss: 3.3428
Epoch [9/	20]	d_loss: 1.2161	g_loss: 0.9055
Epoch [9/	20]	d_loss: 1.1698	g_loss: 1.2545
Epoch [9/	20]	d_loss: 0.7771	g_loss: 2.0362
Epoch [9/	20]	d_loss: 1.0175	g_loss: 1.6533
Epoch [9/	20]	d_loss: 1.0763	g_loss: 1.2488
Epoch [9/	20]	d_loss: 1.2067	g_loss: 4.0500
Epoch [9/	20]	d_loss: 1.4457	g_loss: 1.0013
Epoch [9/	20]	d_loss: 0.6138	g_loss: 1.5349
Epoch [9/	20]	d_loss: 0.6903	g_loss: 2.1889
Epoch [9/	20]	d_loss: 0.8987	g_loss: 1.7895
Epoch [9/	20]	d_loss: 1.1958	g_loss: 0.6613
Epoch [9/	20]	d_loss: 0.9407	g_loss: 1.8264
Epoch [9/	20]	d_loss: 0.9652	g_loss: 1.6092
Epoch [9/	20]	d_loss: 0.7446	g_loss: 1.3745
Epoch [9/	20]	d_loss: 1.0466	g_loss: 3.2333
Epoch [9/	20]	d_loss: 1.4456	g_loss: 2.2510
Epoch [9/	20]	d_loss: 0.6746	g_loss: 1.9958
Epoch [9/	20]	d_loss: 1.1321	g_loss: 2.3777
Epoch [9/	20]	d_loss: 0.8301	g_loss: 2.3469
Epoch [9/	20]	d_loss: 0.7412	g_loss: 1.7729
Epoch [9/	20]	d_loss: 1.2512	g_loss: 1.5619
Epoch [9/	20]	d_loss: 0.9024	g_loss: 2.0391

Epoch [9/	20]	d_loss: 0.6175	g_loss: 3.1353
Epoch [9/	20]	d_loss: 0.9978	g_loss: 2.4990
Epoch [9/	20]	d_loss: 0.6818	g_loss: 2.1180
Epoch [9/	20]	d_loss: 0.5625	g_loss: 1.3802
Epoch [9/	20]	d_loss: 1.0244	g_loss: 1.7958
Epoch [9/	20]	d_loss: 0.9174	g_loss: 1.2820
Epoch [9/	20]	d_loss: 0.7433	g_loss: 1.4434
Epoch [9/	20]	d_loss: 1.3821	g_loss: 2.9227
Epoch [9/	20]	d_loss: 0.7907	g_loss: 1.0174
Epoch [9/	20]	d_loss: 0.7007	g_loss: 3.0953
Epoch [9/	20]	d_loss: 0.8159	g_loss: 2.2924
Epoch [9/	20]	d_loss: 0.9554	g_loss: 2.5253
Epoch [10/	20]	d_loss: 1.0512	g_loss: 1.0499
Epoch [10/	20]	d_loss: 0.8143	g_loss: 2.3451
Epoch [10/	20]	d_loss: 0.8120	g_loss: 2.4712
Epoch [10/	20]	d_loss: 0.9735	g_loss: 2.1034
Epoch [10/	20]	d_loss: 1.0025	g_loss: 2.0604
Epoch [10/	20]	d_loss: 0.6702	g_loss: 2.8112
Epoch [10/	20]	d_loss: 0.8546	g_loss: 1.9547
Epoch [10/	20]	d_loss: 1.2061	g_loss: 1.9312
Epoch [10/	20]	d_loss: 0.9974	g_loss: 2.7466
Epoch [10/	20]	d_loss: 1.0738	g_loss: 3.2056
Epoch [10/	20]	d_loss: 0.9727	g_loss: 1.7171
Epoch [10/	20]	d_loss: 0.6777	g_loss: 1.5499
Epoch [10/	20]	d_loss: 0.7212	g_loss: 2.3411
Epoch [10/	20]	d_loss: 0.6318	g_loss: 1.7620
Epoch [10/	20]	d_loss: 0.5068	g_loss: 2.4609
Epoch [10/	20]	d_loss: 0.6704	g_loss: 1.5372
Epoch [10/	20]	d_loss: 0.6121	g_loss: 2.9131
Epoch [10/	20]	d_loss: 1.4172	g_loss: 1.1579
Epoch [10/	20]	d_loss: 0.5868	g_loss: 2.6120
Epoch [10/	20]	d_loss: 1.0784	g_loss: 1.6508
Epoch [10/	20]	d_loss: 0.8169	g_loss: 2.2331
Epoch [10/	20]	d_loss: 0.8817	g_loss: 1.2021
Epoch [10/	20]	d_loss: 0.6113	g_loss: 1.9642
Epoch [10/	20]	d_loss: 0.6352	g_loss: 1.7044
Epoch [10/	20]	d_loss: 0.6933	g_loss: 2.1638
Epoch [10/	20]	d_loss: 1.0306	g_loss: 1.9590
Epoch [10/	20]	d_loss: 1.1437	g_loss: 2.1098
Epoch [10/	20]	d_loss: 1.3516	g_loss: 2.4633
Epoch [10/	20]	d_loss: 1.0199	g_loss: 2.3237
Epoch [10/	20]	d_loss: 1.1409	g_loss: 2.4938
Epoch [10/	20]	d_loss: 0.7194	g_loss: 1.4005
Epoch [10/	20]	d_loss: 0.5241	g_loss: 1.8518
Epoch [10/	20]	d_loss: 1.0541	g_loss: 2.3646
Epoch [10/	20]	d_loss: 0.8564	g_loss: 3.2623
Epoch [10/	20]	d_loss: 1.2069	g_loss: 1.3519
Epoch [10/	20]	d_loss: 0.8306	g_loss: 2.3960

Epoch [10/	20]	d_loss: 0.7389	g_loss: 1.7327
Epoch [10/	20]	d_loss: 0.7164	g_loss: 0.9886
Epoch [10/	20]	d_loss: 0.8201	g_loss: 2.0292
Epoch [10/	20]	d_loss: 0.7873	g_loss: 2.0382
Epoch [10/	20]	d_loss: 1.5792	g_loss: 1.2192
Epoch [10/	20]	d_loss: 0.6874	g_loss: 1.1817
Epoch [10/	20]	d_loss: 1.5140	g_loss: 1.4178
Epoch [10/	20]	d_loss: 1.1923	g_loss: 1.4457
Epoch [10/	20]	d_loss: 1.0105	g_loss: 2.7703
Epoch [10/	20]	d_loss: 0.7807	g_loss: 1.7882
Epoch [10/	20]	d_loss: 0.7691	g_loss: 1.9226
Epoch [10/	20]	d_loss: 1.2896	g_loss: 2.5494
Epoch [10/	20]	d_loss: 0.8661	g_loss: 4.0807
Epoch [10/	20]	d_loss: 0.9140	g_loss: 2.4824
Epoch [10/	20]	d_loss: 1.4228	g_loss: 2.1107
Epoch [10/	20]	d_loss: 1.3455	g_loss: 1.6029
Epoch [10/	20]	d_loss: 0.6939	g_loss: 3.2343
Epoch [10/	20]	d_loss: 1.2694	g_loss: 0.8288
Epoch [10/	20]	d_loss: 0.8768	g_loss: 1.9760
Epoch [10/	20]	d_loss: 0.8660	g_loss: 2.6614
Epoch [10/	20]	d_loss: 0.9840	g_loss: 1.8546
Epoch [11/	20]	d_loss: 1.0583	g_loss: 1.1410
Epoch [11/	20]	d_loss: 1.0229	g_loss: 1.2665
Epoch [11/	20]	d_loss: 1.3764	g_loss: 1.1308
Epoch [11/	20]	d_loss: 0.8307	g_loss: 1.8961
Epoch [11/	20]	d_loss: 0.7443	g_loss: 2.3635
Epoch [11/	20]	d_loss: 0.6494	g_loss: 2.9373
Epoch [11/	20]	d_loss: 0.8008	g_loss: 2.6747
Epoch [11/	20]	d_loss: 0.6632	g_loss: 1.3517
Epoch [11/	20]	d_loss: 0.8178	g_loss: 2.4439
Epoch [11/	20]	d_loss: 0.8109	g_loss: 1.7945
Epoch [11/	20]	d_loss: 0.7457	g_loss: 2.5001
Epoch [11/	20]	d_loss: 1.0695	g_loss: 1.5002
Epoch [11/	20]	d_loss: 0.7995	g_loss: 1.8809
Epoch [11/	20]	d_loss: 0.4994	g_loss: 2.7949
Epoch [11/	20]	d_loss: 1.3293	g_loss: 1.9701
Epoch [11/	20]	d_loss: 1.1794	g_loss: 1.2487
Epoch [11/	20]	d_loss: 0.7724	g_loss: 2.1893
Epoch [11/	20]	d_loss: 1.1044	g_loss: 2.0210
Epoch [11/	20]	d_loss: 1.2017	g_loss: 1.2567
Epoch [11/	20]	d_loss: 1.1828	g_loss: 1.7897
Epoch [11/	20]	d_loss: 1.0272	g_loss: 1.7311
Epoch [11/	20]	d_loss: 0.7241	g_loss: 1.6426
Epoch [11/	20]	d_loss: 1.0612	g_loss: 1.8093
Epoch [11/	20]	d_loss: 0.9432	g_loss: 3.3945
Epoch [11/	20]	d_loss: 1.0017	g_loss: 1.6286
Epoch [11/	20]	d_loss: 0.6023	g_loss: 2.5788
Epoch [11/	20]	d_loss: 0.9020	g_loss: 1.9261

Epoch [11/	20]		d_loss: 0.7430		g_loss: 2.5351
Epoch [11/	20]		d_loss: 0.6537		g_loss: 3.9969
Epoch [11/	20]		d_loss: 0.7229		g_loss: 2.8053
Epoch [11/	20]		d_loss: 1.1724		g_loss: 2.9201
Epoch [11/	20]		d_loss: 0.7322		g_loss: 1.7223
Epoch [11/	20]		d_loss: 0.7636		g_loss: 2.1063
Epoch [11/	20]		d_loss: 0.6407		g_loss: 3.8544
Epoch [11/	20]		d_loss: 1.3011		g_loss: 1.2367
Epoch [11/	20]		d_loss: 0.8339		g_loss: 2.4530
Epoch [11/	20]		d_loss: 1.1833		g_loss: 2.5081
Epoch [11/	20]		d_loss: 0.7424		g_loss: 2.0304
Epoch [11/	20]		d_loss: 0.5180		g_loss: 1.8731
Epoch [11/	20]		d_loss: 0.7543		g_loss: 2.2796
Epoch [11/	20]		d_loss: 0.7932		g_loss: 0.9287
Epoch [11/	20]		d_loss: 1.0160		g_loss: 1.8964
Epoch [11/	20]		d_loss: 0.6824		g_loss: 2.6888
Epoch [11/	20]		d_loss: 0.5437		g_loss: 2.6340
Epoch [11/	20]		d_loss: 0.5948		g_loss: 2.4756
Epoch [11/	20]		d_loss: 0.9285		g_loss: 2.2105
Epoch [11/	20]		d_loss: 0.5390		g_loss: 2.7158
Epoch [11/	20]		d_loss: 0.8970		g_loss: 2.4838
Epoch [11/	20]		d_loss: 1.1088		g_loss: 1.8450
Epoch [11/	20]		d_loss: 1.0986		g_loss: 1.1351
Epoch [11/	20]		d_loss: 0.9969		g_loss: 1.3477
Epoch [11/	20]		d_loss: 0.8520		g_loss: 2.0100
Epoch [11/	20]		d_loss: 0.9686		g_loss: 1.7592
Epoch [11/	20]		d_loss: 1.0549		g_loss: 1.9004
Epoch [11/	20]		d_loss: 0.8198		g_loss: 2.1203
Epoch [11/	20]		d_loss: 0.9208		g_loss: 2.0379
Epoch [11/	20]		d_loss: 0.8502		g_loss: 1.3376
Epoch [12/	20]		d_loss: 0.8349		g_loss: 1.6693
Epoch [12/	20]		d_loss: 0.9142		g_loss: 2.2833
Epoch [12/	20]		d_loss: 0.9239		g_loss: 2.6598
Epoch [12/	20]		d_loss: 0.7118		g_loss: 1.8293
Epoch [12/	20]		d_loss: 0.9603		g_loss: 1.6718
Epoch [12/	20]		d_loss: 0.9519		g_loss: 2.5433
Epoch [12/	20]		d_loss: 2.1665		g_loss: 1.0754
Epoch [12/	20]		d_loss: 1.4691		g_loss: 1.1451
Epoch [12/	20]		d_loss: 0.6288		g_loss: 2.1011
Epoch [12/	20]		d_loss: 0.9008		g_loss: 2.6876
Epoch [12/	20]		d_loss: 0.6861		g_loss: 2.4360
Epoch [12/	20]		d_loss: 0.6669		g_loss: 2.6263
Epoch [12/	20]		d_loss: 0.6634		g_loss: 2.2835
Epoch [12/	20]		d_loss: 0.5989		g_loss: 1.7570
Epoch [12/	20]		d_loss: 0.8619		g_loss: 1.9932
Epoch [12/	20]		d_loss: 0.8641		g_loss: 2.2038
Epoch [12/	20]		d_loss: 1.3999		g_loss: 2.7109
Epoch [12/	20]		d_loss: 0.9189		g_loss: 1.6294

Epoch [12/	20]	d_loss: 0.6185	g_loss: 1.7377
Epoch [12/	20]	d_loss: 0.7670	g_loss: 1.5876
Epoch [12/	20]	d_loss: 0.6118	g_loss: 2.4857
Epoch [12/	20]	d_loss: 1.0499	g_loss: 2.1376
Epoch [12/	20]	d_loss: 0.9243	g_loss: 1.1888
Epoch [12/	20]	d_loss: 0.6717	g_loss: 0.9377
Epoch [12/	20]	d_loss: 0.6794	g_loss: 3.0587
Epoch [12/	20]	d_loss: 0.7906	g_loss: 1.6634
Epoch [12/	20]	d_loss: 1.1769	g_loss: 1.5246
Epoch [12/	20]	d_loss: 0.7740	g_loss: 1.4364
Epoch [12/	20]	d_loss: 0.8622	g_loss: 3.1335
Epoch [12/	20]	d_loss: 0.6151	g_loss: 2.7097
Epoch [12/	20]	d_loss: 1.2825	g_loss: 2.1065
Epoch [12/	20]	d_loss: 0.7534	g_loss: 2.0775
Epoch [12/	20]	d_loss: 0.5110	g_loss: 3.4616
Epoch [12/	20]	d_loss: 0.9491	g_loss: 1.0655
Epoch [12/	20]	d_loss: 0.8709	g_loss: 3.5972
Epoch [12/	20]	d_loss: 0.7070	g_loss: 2.6101
Epoch [12/	20]	d_loss: 0.7544	g_loss: 2.9295
Epoch [12/	20]	d_loss: 0.8358	g_loss: 2.3395
Epoch [12/	20]	d_loss: 0.6654	g_loss: 2.6731
Epoch [12/	20]	d_loss: 0.7862	g_loss: 1.7343
Epoch [12/	20]	d_loss: 0.8280	g_loss: 1.6613
Epoch [12/	20]	d_loss: 0.7375	g_loss: 2.1069
Epoch [12/	20]	d_loss: 0.8701	g_loss: 1.2782
Epoch [12/	20]	d_loss: 0.9104	g_loss: 1.8193
Epoch [12/	20]	d_loss: 1.1433	g_loss: 1.7419
Epoch [12/	20]	d_loss: 1.1412	g_loss: 1.2031
Epoch [12/	20]	d_loss: 0.5641	g_loss: 2.2382
Epoch [12/	20]	d_loss: 0.8329	g_loss: 1.6403
Epoch [12/	20]	d_loss: 0.6120	g_loss: 2.5593
Epoch [12/	20]	d_loss: 0.8342	g_loss: 1.3488
Epoch [12/	20]	d_loss: 0.6363	g_loss: 1.3277
Epoch [12/	20]	d_loss: 1.6017	g_loss: 1.7677
Epoch [12/	20]	d_loss: 0.4985	g_loss: 2.1848
Epoch [12/	20]	d_loss: 0.8673	g_loss: 1.6973
Epoch [12/	20]	d_loss: 1.1007	g_loss: 2.0663
Epoch [12/	20]	d_loss: 1.7783	g_loss: 2.9400
Epoch [12/	20]	d_loss: 0.8479	g_loss: 1.3612
Epoch [13/	20]	d_loss: 1.0811	g_loss: 1.8548
Epoch [13/	20]	d_loss: 1.0037	g_loss: 1.5085
Epoch [13/	20]	d_loss: 0.7087	g_loss: 1.9632
Epoch [13/	20]	d_loss: 1.0003	g_loss: 2.5180
Epoch [13/	20]	d_loss: 1.2275	g_loss: 1.5070
Epoch [13/	20]	d_loss: 0.9931	g_loss: 2.4093
Epoch [13/	20]	d_loss: 0.7622	g_loss: 1.7991
Epoch [13/	20]	d_loss: 0.7369	g_loss: 1.7393
Epoch [13/	20]	d_loss: 0.6865	g_loss: 1.4352

Epoch [13/	20]	d_loss: 0.8622	g_loss: 3.1865
Epoch [13/	20]	d_loss: 0.8305	g_loss: 1.3625
Epoch [13/	20]	d_loss: 0.6657	g_loss: 1.7578
Epoch [13/	20]	d_loss: 0.9207	g_loss: 3.3307
Epoch [13/	20]	d_loss: 0.5324	g_loss: 2.3157
Epoch [13/	20]	d_loss: 0.7678	g_loss: 2.7930
Epoch [13/	20]	d_loss: 0.7884	g_loss: 2.6841
Epoch [13/	20]	d_loss: 0.6324	g_loss: 2.4080
Epoch [13/	20]	d_loss: 0.9327	g_loss: 2.4433
Epoch [13/	20]	d_loss: 0.7720	g_loss: 1.5235
Epoch [13/	20]	d_loss: 0.8538	g_loss: 1.4712
Epoch [13/	20]	d_loss: 0.6654	g_loss: 2.2614
Epoch [13/	20]	d_loss: 0.7834	g_loss: 3.4943
Epoch [13/	20]	d_loss: 0.6431	g_loss: 2.2454
Epoch [13/	20]	d_loss: 0.6543	g_loss: 2.5686
Epoch [13/	20]	d_loss: 0.8663	g_loss: 1.6647
Epoch [13/	20]	d_loss: 0.7846	g_loss: 1.6436
Epoch [13/	20]	d_loss: 0.9141	g_loss: 1.6811
Epoch [13/	20]	d_loss: 0.9476	g_loss: 2.6255
Epoch [13/	20]	d_loss: 0.8612	g_loss: 2.3644
Epoch [13/	20]	d_loss: 0.6452	g_loss: 1.9365
Epoch [13/	20]	d_loss: 0.8770	g_loss: 2.4096
Epoch [13/	20]	d_loss: 0.7452	g_loss: 2.6177
Epoch [13/	20]	d_loss: 0.7976	g_loss: 1.4218
Epoch [13/	20]	d_loss: 1.0160	g_loss: 2.4934
Epoch [13/	20]	d_loss: 1.0639	g_loss: 2.4466
Epoch [13/	20]	d_loss: 0.7034	g_loss: 2.1513
Epoch [13/	20]	d_loss: 1.4920	g_loss: 2.6873
Epoch [13/	20]	d_loss: 1.3166	g_loss: 1.5136
Epoch [13/	20]	d_loss: 0.6524	g_loss: 1.3054
Epoch [13/	20]	d_loss: 1.1444	g_loss: 1.7232
Epoch [13/	20]	d_loss: 0.9726	g_loss: 1.8137
Epoch [13/	20]	d_loss: 0.8719	g_loss: 1.7782
Epoch [13/	20]	d_loss: 0.6694	g_loss: 1.9829
Epoch [13/	20]	d_loss: 0.9114	g_loss: 1.7468
Epoch [13/	20]	d_loss: 1.0380	g_loss: 2.9024
Epoch [13/	20]	d_loss: 0.8718	g_loss: 2.0894
Epoch [13/	20]	d_loss: 0.5736	g_loss: 1.8192
Epoch [13/	20]	d_loss: 1.2947	g_loss: 2.0543
Epoch [13/	20]	d_loss: 1.3861	g_loss: 2.2540
Epoch [13/	20]	d_loss: 0.8377	g_loss: 2.8135
Epoch [13/	20]	d_loss: 0.5706	g_loss: 3.2303
Epoch [13/	20]	d_loss: 1.2595	g_loss: 2.1464
Epoch [13/	20]	d_loss: 0.7651	g_loss: 2.3553
Epoch [13/	20]	d_loss: 1.1259	g_loss: 2.8996
Epoch [13/	20]	d_loss: 0.6878	g_loss: 1.7747
Epoch [13/	20]	d_loss: 1.1499	g_loss: 2.2945
Epoch [13/	20]	d_loss: 0.9429	g_loss: 2.1055

Epoch [14/	20]	d_loss: 1.2740	g_loss: 1.8179
Epoch [14/	20]	d_loss: 0.9777	g_loss: 1.5269
Epoch [14/	20]	d_loss: 0.7362	g_loss: 2.0298
Epoch [14/	20]	d_loss: 0.7028	g_loss: 1.9201
Epoch [14/	20]	d_loss: 0.8644	g_loss: 2.1528
Epoch [14/	20]	d_loss: 0.9921	g_loss: 1.1206
Epoch [14/	20]	d_loss: 0.7099	g_loss: 1.7517
Epoch [14/	20]	d_loss: 0.7797	g_loss: 2.5758
Epoch [14/	20]	d_loss: 0.8123	g_loss: 3.0986
Epoch [14/	20]	d_loss: 1.0557	g_loss: 1.9375
Epoch [14/	20]	d_loss: 1.0205	g_loss: 1.1121
Epoch [14/	20]	d_loss: 0.5840	g_loss: 2.9331
Epoch [14/	20]	d_loss: 0.6891	g_loss: 1.6905
Epoch [14/	20]	d_loss: 0.6430	g_loss: 2.3173
Epoch [14/	20]	d_loss: 0.7533	g_loss: 1.9212
Epoch [14/	20]	d_loss: 0.7147	g_loss: 2.8714
Epoch [14/	20]	d_loss: 1.0837	g_loss: 3.0381
Epoch [14/	20]	d_loss: 0.5956	g_loss: 2.4516
Epoch [14/	20]	d_loss: 0.5916	g_loss: 1.1084
Epoch [14/	20]	d_loss: 1.7104	g_loss: 1.9082
Epoch [14/	20]	d_loss: 0.7259	g_loss: 1.9869
Epoch [14/	20]	d_loss: 0.7081	g_loss: 1.9809
Epoch [14/	20]	d_loss: 0.8266	g_loss: 2.2862
Epoch [14/	20]	d_loss: 1.1873	g_loss: 1.1504
Epoch [14/	20]	d_loss: 0.6501	g_loss: 2.5667
Epoch [14/	20]	d_loss: 0.5962	g_loss: 1.8413
Epoch [14/	20]	d_loss: 0.5375	g_loss: 2.4155
Epoch [14/	20]	d_loss: 0.7838	g_loss: 3.0000
Epoch [14/	20]	d_loss: 0.4923	g_loss: 3.4247
Epoch [14/	20]	d_loss: 0.8401	g_loss: 1.6430
Epoch [14/	20]	d_loss: 0.7199	g_loss: 1.8397
Epoch [14/	20]	d_loss: 0.5308	g_loss: 1.4427
Epoch [14/	20]	d_loss: 0.9072	g_loss: 1.3427
Epoch [14/	20]	d_loss: 0.9753	g_loss: 3.2659
Epoch [14/	20]	d_loss: 1.0735	g_loss: 1.4396
Epoch [14/	20]	d_loss: 1.1187	g_loss: 2.8004
Epoch [14/	20]	d_loss: 0.9423	g_loss: 2.4187
Epoch [14/	20]	d_loss: 0.7413	g_loss: 2.4858
Epoch [14/	20]	d_loss: 1.3018	g_loss: 1.6220
Epoch [14/	20]	d_loss: 0.9945	g_loss: 1.1113
Epoch [14/	20]	d_loss: 0.5971	g_loss: 1.2396
Epoch [14/	20]	d_loss: 0.5772	g_loss: 2.3390
Epoch [14/	20]	d_loss: 0.8171	g_loss: 2.5582
Epoch [14/	20]	d_loss: 1.1975	g_loss: 1.0512
Epoch [14/	20]	d_loss: 0.9063	g_loss: 2.7857
Epoch [14/	20]	d_loss: 0.5283	g_loss: 2.8671
Epoch [14/	20]	d_loss: 0.8424	g_loss: 1.4731
Epoch [14/	20]	d_loss: 0.5966	g_loss: 2.4843

Epoch [14/	20]	d_loss: 0.9153	g_loss: 2.7967
Epoch [14/	20]	d_loss: 0.9535	g_loss: 2.0965
Epoch [14/	20]	d_loss: 0.7422	g_loss: 1.5148
Epoch [14/	20]	d_loss: 0.8377	g_loss: 2.5290
Epoch [14/	20]	d_loss: 1.0618	g_loss: 1.1808
Epoch [14/	20]	d_loss: 0.9344	g_loss: 1.3381
Epoch [14/	20]	d_loss: 0.5994	g_loss: 1.4026
Epoch [14/	20]	d_loss: 1.3936	g_loss: 2.4075
Epoch [14/	20]	d_loss: 1.0295	g_loss: 0.7976
Epoch [15/	20]	d_loss: 0.5931	g_loss: 2.0979
Epoch [15/	20]	d_loss: 0.5902	g_loss: 1.8700
Epoch [15/	20]	d_loss: 0.6703	g_loss: 2.5686
Epoch [15/	20]	d_loss: 0.8310	g_loss: 2.6152
Epoch [15/	20]	d_loss: 0.8090	g_loss: 2.1511
Epoch [15/	20]	d_loss: 0.7203	g_loss: 2.4799
Epoch [15/	20]	d_loss: 0.5369	g_loss: 1.5427
Epoch [15/	20]	d_loss: 0.8177	g_loss: 2.5534
Epoch [15/	20]	d_loss: 0.6210	g_loss: 2.0961
Epoch [15/	20]	d_loss: 1.2136	g_loss: 1.6601
Epoch [15/	20]	d_loss: 0.6623	g_loss: 2.1093
Epoch [15/	20]	d_loss: 0.6578	g_loss: 2.3748
Epoch [15/	20]	d_loss: 0.8960	g_loss: 1.2108
Epoch [15/	20]	d_loss: 0.9907	g_loss: 1.9481
Epoch [15/	20]	d_loss: 0.8998	g_loss: 1.9503
Epoch [15/	20]	d_loss: 0.8386	g_loss: 1.8928
Epoch [15/	20]	d_loss: 1.0743	g_loss: 2.1755
Epoch [15/	20]	d_loss: 1.1427	g_loss: 2.5023
Epoch [15/	20]	d_loss: 0.5590	g_loss: 2.5243
Epoch [15/	20]	d_loss: 0.4692	g_loss: 4.0102
Epoch [15/	20]	d_loss: 1.1474	g_loss: 1.8025
Epoch [15/	20]	d_loss: 1.2782	g_loss: 2.0035
Epoch [15/	20]	d_loss: 0.7952	g_loss: 3.4628
Epoch [15/	20]	d_loss: 0.6008	g_loss: 3.2108
Epoch [15/	20]	d_loss: 0.6210	g_loss: 1.8595
Epoch [15/	20]	d_loss: 0.6277	g_loss: 3.1413
Epoch [15/	20]	d_loss: 0.6632	g_loss: 1.3418
Epoch [15/	20]	d_loss: 0.5386	g_loss: 2.1345
Epoch [15/	20]	d_loss: 0.8168	g_loss: 3.5440
Epoch [15/	20]	d_loss: 1.0598	g_loss: 1.9390
Epoch [15/	20]	d_loss: 0.9321	g_loss: 2.2803
Epoch [15/	20]	d_loss: 0.6276	g_loss: 2.4134
Epoch [15/	20]	d_loss: 0.5423	g_loss: 1.6639
Epoch [15/	20]	d_loss: 0.8474	g_loss: 2.1702
Epoch [15/	20]	d_loss: 0.5195	g_loss: 2.8451
Epoch [15/	20]	d_loss: 0.6933	g_loss: 2.1381
Epoch [15/	20]	d_loss: 1.0315	g_loss: 2.8259
Epoch [15/	20]	d_loss: 0.6441	g_loss: 1.7524
Epoch [15/	20]	d_loss: 1.4911	g_loss: 1.6668

Epoch [15/	20]	d_loss: 1.0644	g_loss: 2.9486
Epoch [15/	20]	d_loss: 0.6567	g_loss: 2.8730
Epoch [15/	20]	d_loss: 0.6012	g_loss: 3.8355
Epoch [15/	20]	d_loss: 0.5520	g_loss: 2.2558
Epoch [15/	20]	d_loss: 0.6177	g_loss: 2.7650
Epoch [15/	20]	d_loss: 0.7465	g_loss: 2.6714
Epoch [15/	20]	d_loss: 1.1038	g_loss: 1.4019
Epoch [15/	20]	d_loss: 0.5039	g_loss: 2.2442
Epoch [15/	20]	d_loss: 0.8809	g_loss: 0.7716
Epoch [15/	20]	d_loss: 0.7663	g_loss: 2.7180
Epoch [15/	20]	d_loss: 1.5398	g_loss: 2.3821
Epoch [15/	20]	d_loss: 1.0225	g_loss: 3.1515
Epoch [15/	20]	d_loss: 0.6483	g_loss: 2.4153
Epoch [15/	20]	d_loss: 0.6063	g_loss: 3.0700
Epoch [15/	20]	d_loss: 0.7834	g_loss: 0.7998
Epoch [15/	20]	d_loss: 0.9736	g_loss: 1.3293
Epoch [15/	20]	d_loss: 0.9427	g_loss: 2.3545
Epoch [15/	20]	d_loss: 0.6711	g_loss: 2.2321
Epoch [16/	20]	d_loss: 0.8058	g_loss: 2.3772
Epoch [16/	20]	d_loss: 0.6469	g_loss: 1.4919
Epoch [16/	20]	d_loss: 0.6250	g_loss: 2.6132
Epoch [16/	20]	d_loss: 0.5387	g_loss: 3.0888
Epoch [16/	20]	d_loss: 0.7706	g_loss: 2.3900
Epoch [16/	20]	d_loss: 0.5155	g_loss: 1.3384
Epoch [16/	20]	d_loss: 0.6055	g_loss: 2.0808
Epoch [16/	20]	d_loss: 1.0702	g_loss: 1.1748
Epoch [16/	20]	d_loss: 1.0125	g_loss: 1.3581
Epoch [16/	20]	d_loss: 0.5400	g_loss: 3.1761
Epoch [16/	20]	d_loss: 0.4674	g_loss: 3.4390
Epoch [16/	20]	d_loss: 0.8151	g_loss: 3.4030
Epoch [16/	20]	d_loss: 0.7489	g_loss: 2.8332
Epoch [16/	20]	d_loss: 1.0263	g_loss: 3.0564
Epoch [16/	20]	d_loss: 0.5276	g_loss: 4.0774
Epoch [16/	20]	d_loss: 0.8042	g_loss: 1.4352
Epoch [16/	20]	d_loss: 1.2452	g_loss: 1.8593
Epoch [16/	20]	d_loss: 0.7803	g_loss: 4.5005
Epoch [16/	20]	d_loss: 0.8892	g_loss: 2.3830
Epoch [16/	20]	d_loss: 0.6096	g_loss: 3.2828
Epoch [16/	20]	d_loss: 0.7968	g_loss: 3.4958
Epoch [16/	20]	d_loss: 0.7609	g_loss: 2.8309
Epoch [16/	20]	d_loss: 1.0750	g_loss: 1.7746
Epoch [16/	20]	d_loss: 0.7031	g_loss: 2.7837
Epoch [16/	20]	d_loss: 0.8447	g_loss: 1.5464
Epoch [16/	20]	d_loss: 0.4187	g_loss: 2.4520
Epoch [16/	20]	d_loss: 0.6950	g_loss: 2.0474
Epoch [16/	20]	d_loss: 0.5338	g_loss: 2.6289
Epoch [16/	20]	d_loss: 1.6015	g_loss: 3.0962
Epoch [16/	20]	d_loss: 1.2246	g_loss: 2.8718

Epoch [16/	20]	d_loss: 1.1026	g_loss: 3.6262
Epoch [16/	20]	d_loss: 0.7506	g_loss: 1.6233
Epoch [16/	20]	d_loss: 0.7807	g_loss: 2.3179
Epoch [16/	20]	d_loss: 0.7641	g_loss: 1.4597
Epoch [16/	20]	d_loss: 0.4897	g_loss: 2.4759
Epoch [16/	20]	d_loss: 0.6194	g_loss: 1.1375
Epoch [16/	20]	d_loss: 0.5781	g_loss: 1.3922
Epoch [16/	20]	d_loss: 1.1199	g_loss: 1.1769
Epoch [16/	20]	d_loss: 1.2359	g_loss: 2.3224
Epoch [16/	20]	d_loss: 0.5815	g_loss: 2.1328
Epoch [16/	20]	d_loss: 1.1934	g_loss: 2.0734
Epoch [16/	20]	d_loss: 0.9385	g_loss: 2.6502
Epoch [16/	20]	d_loss: 0.5644	g_loss: 2.1051
Epoch [16/	20]	d_loss: 0.8662	g_loss: 1.5439
Epoch [16/	20]	d_loss: 0.5457	g_loss: 1.1409
Epoch [16/	20]	d_loss: 0.7046	g_loss: 1.7774
Epoch [16/	20]	d_loss: 0.8389	g_loss: 2.6264
Epoch [16/	20]	d_loss: 0.7247	g_loss: 2.9109
Epoch [16/	20]	d_loss: 0.8420	g_loss: 3.0485
Epoch [16/	20]	d_loss: 0.9493	g_loss: 3.6272
Epoch [16/	20]	d_loss: 0.7761	g_loss: 2.3473
Epoch [16/	20]	d_loss: 0.5224	g_loss: 2.6953
Epoch [16/	20]	d_loss: 0.8810	g_loss: 2.0656
Epoch [16/	20]	d_loss: 1.1909	g_loss: 2.6195
Epoch [16/	20]	d_loss: 0.7435	g_loss: 2.3253
Epoch [16/	20]	d_loss: 0.8058	g_loss: 2.1462
Epoch [16/	20]	d_loss: 0.5116	g_loss: 3.2302
Epoch [17/	20]	d_loss: 0.5442	g_loss: 1.4460
Epoch [17/	20]	d_loss: 0.5413	g_loss: 3.3535
Epoch [17/	20]	d_loss: 0.5469	g_loss: 2.8652
Epoch [17/	20]	d_loss: 0.8004	g_loss: 2.1881
Epoch [17/	20]	d_loss: 0.6837	g_loss: 2.2428
Epoch [17/	20]	d_loss: 0.7177	g_loss: 2.4053
Epoch [17/	20]	d_loss: 0.7028	g_loss: 3.2445
Epoch [17/	20]	d_loss: 0.5630	g_loss: 3.1835
Epoch [17/	20]	d_loss: 0.7838	g_loss: 3.1248
Epoch [17/	20]	d_loss: 0.9326	g_loss: 1.8044
Epoch [17/	20]	d_loss: 0.6480	g_loss: 2.0256
Epoch [17/	20]	d_loss: 0.6951	g_loss: 1.7096
Epoch [17/	20]	d_loss: 0.8858	g_loss: 3.1829
Epoch [17/	20]	d_loss: 0.5658	g_loss: 2.6337
Epoch [17/	20]	d_loss: 0.8150	g_loss: 2.2932
Epoch [17/	20]	d_loss: 0.8911	g_loss: 2.3870
Epoch [17/	20]	d_loss: 0.6673	g_loss: 3.2768
Epoch [17/	20]	d_loss: 0.5074	g_loss: 2.0498
Epoch [17/	20]	d_loss: 0.9728	g_loss: 2.7461
Epoch [17/	20]	d_loss: 0.6860	g_loss: 3.4419
Epoch [17/	20]	d_loss: 0.5877	g_loss: 1.8639

Epoch [17/	20]	d_loss: 0.6915	g_loss: 1.8448
Epoch [17/	20]	d_loss: 0.6018	g_loss: 3.1527
Epoch [17/	20]	d_loss: 0.5820	g_loss: 3.0992
Epoch [17/	20]	d_loss: 0.8517	g_loss: 2.4713
Epoch [17/	20]	d_loss: 0.8019	g_loss: 1.7650
Epoch [17/	20]	d_loss: 0.6783	g_loss: 1.8447
Epoch [17/	20]	d_loss: 1.1697	g_loss: 1.6909
Epoch [17/	20]	d_loss: 1.3140	g_loss: 1.9916
Epoch [17/	20]	d_loss: 0.7275	g_loss: 2.1595
Epoch [17/	20]	d_loss: 0.6965	g_loss: 2.0113
Epoch [17/	20]	d_loss: 0.5738	g_loss: 2.9806
Epoch [17/	20]	d_loss: 0.3984	g_loss: 2.4970
Epoch [17/	20]	d_loss: 0.8555	g_loss: 2.3000
Epoch [17/	20]	d_loss: 0.5670	g_loss: 3.7274
Epoch [17/	20]	d_loss: 0.9608	g_loss: 2.5820
Epoch [17/	20]	d_loss: 0.8849	g_loss: 3.2872
Epoch [17/	20]	d_loss: 0.7786	g_loss: 1.5698
Epoch [17/	20]	d_loss: 0.7081	g_loss: 1.9964
Epoch [17/	20]	d_loss: 0.9466	g_loss: 2.5659
Epoch [17/	20]	d_loss: 0.6524	g_loss: 2.5837
Epoch [17/	20]	d_loss: 0.5438	g_loss: 1.3879
Epoch [17/	20]	d_loss: 0.6652	g_loss: 1.5976
Epoch [17/	20]	d_loss: 0.6218	g_loss: 2.9459
Epoch [17/	20]	d_loss: 0.9822	g_loss: 1.5928
Epoch [17/	20]	d_loss: 0.5721	g_loss: 2.6007
Epoch [17/	20]	d_loss: 0.5330	g_loss: 1.8301
Epoch [17/	20]	d_loss: 0.6160	g_loss: 2.3702
Epoch [17/	20]	d_loss: 1.1669	g_loss: 2.4051
Epoch [17/	20]	d_loss: 0.6798	g_loss: 2.0011
Epoch [17/	20]	d_loss: 1.3019	g_loss: 2.9528
Epoch [17/	20]	d_loss: 0.5732	g_loss: 2.1153
Epoch [17/	20]	d_loss: 0.7787	g_loss: 3.2821
Epoch [17/	20]	d_loss: 0.9609	g_loss: 2.0011
Epoch [17/	20]	d_loss: 0.5489	g_loss: 2.7939
Epoch [17/	20]	d_loss: 0.8883	g_loss: 2.0143
Epoch [17/	20]	d_loss: 0.7772	g_loss: 2.3836
Epoch [18/	20]	d_loss: 0.7827	g_loss: 2.3279
Epoch [18/	20]	d_loss: 0.6529	g_loss: 2.5776
Epoch [18/	20]	d_loss: 1.0637	g_loss: 3.3406
Epoch [18/	20]	d_loss: 0.7554	g_loss: 2.2833
Epoch [18/	20]	d_loss: 1.6443	g_loss: 2.3834
Epoch [18/	20]	d_loss: 0.5132	g_loss: 3.2191
Epoch [18/	20]	d_loss: 0.5532	g_loss: 3.2277
Epoch [18/	20]	d_loss: 0.7034	g_loss: 2.5730
Epoch [18/	20]	d_loss: 1.0738	g_loss: 2.2131
Epoch [18/	20]	d_loss: 1.0019	g_loss: 1.6097
Epoch [18/	20]	d_loss: 1.0275	g_loss: 2.6202
Epoch [18/	20]	d_loss: 0.7459	g_loss: 2.0738

Epoch [18/	20]	d_loss: 0.8917	g_loss: 2.8130
Epoch [18/	20]	d_loss: 0.7123	g_loss: 2.4916
Epoch [18/	20]	d_loss: 1.3290	g_loss: 1.9162
Epoch [18/	20]	d_loss: 0.8120	g_loss: 3.9262
Epoch [18/	20]	d_loss: 1.0496	g_loss: 3.0416
Epoch [18/	20]	d_loss: 0.9931	g_loss: 1.4097
Epoch [18/	20]	d_loss: 0.7568	g_loss: 1.5599
Epoch [18/	20]	d_loss: 0.6217	g_loss: 2.8971
Epoch [18/	20]	d_loss: 0.5928	g_loss: 3.5630
Epoch [18/	20]	d_loss: 0.8999	g_loss: 1.1092
Epoch [18/	20]	d_loss: 0.4923	g_loss: 3.8426
Epoch [18/	20]	d_loss: 0.7802	g_loss: 2.8676
Epoch [18/	20]	d_loss: 0.8009	g_loss: 3.7081
Epoch [18/	20]	d_loss: 0.7012	g_loss: 2.5884
Epoch [18/	20]	d_loss: 1.1585	g_loss: 3.7037
Epoch [18/	20]	d_loss: 0.7057	g_loss: 2.7349
Epoch [18/	20]	d_loss: 0.8640	g_loss: 1.7636
Epoch [18/	20]	d_loss: 0.5208	g_loss: 3.2720
Epoch [18/	20]	d_loss: 0.5190	g_loss: 2.4661
Epoch [18/	20]	d_loss: 0.7642	g_loss: 1.9514
Epoch [18/	20]	d_loss: 0.5865	g_loss: 2.8906
Epoch [18/	20]	d_loss: 0.6109	g_loss: 3.4088
Epoch [18/	20]	d_loss: 0.5690	g_loss: 1.9385
Epoch [18/	20]	d_loss: 0.6005	g_loss: 2.6348
Epoch [18/	20]	d_loss: 0.6583	g_loss: 2.8178
Epoch [18/	20]	d_loss: 0.7407	g_loss: 1.3495
Epoch [18/	20]	d_loss: 0.9958	g_loss: 2.0336
Epoch [18/	20]	d_loss: 0.7320	g_loss: 3.2602
Epoch [18/	20]	d_loss: 0.8400	g_loss: 2.0187
Epoch [18/	20]	d_loss: 0.6358	g_loss: 3.6595
Epoch [18/	20]	d_loss: 0.6716	g_loss: 3.4455
Epoch [18/	20]	d_loss: 0.6674	g_loss: 2.1010
Epoch [18/	20]	d_loss: 0.9175	g_loss: 2.0061
Epoch [18/	20]	d_loss: 0.7876	g_loss: 2.4048
Epoch [18/	20]	d_loss: 1.0223	g_loss: 2.0445
Epoch [18/	20]	d_loss: 0.6393	g_loss: 2.1354
Epoch [18/	20]	d_loss: 0.6395	g_loss: 2.2431
Epoch [18/	20]	d_loss: 0.7933	g_loss: 2.1143
Epoch [18/	20]	d_loss: 0.5078	g_loss: 3.0505
Epoch [18/	20]	d_loss: 0.7487	g_loss: 2.0351
Epoch [18/	20]	d_loss: 0.6201	g_loss: 2.6515
Epoch [18/	20]	d_loss: 0.6549	g_loss: 3.0692
Epoch [18/	20]	d_loss: 0.6596	g_loss: 2.7784
Epoch [18/	20]	d_loss: 0.6770	g_loss: 1.3617
Epoch [18/	20]	d_loss: 0.5012	g_loss: 3.7108
Epoch [19/	20]	d_loss: 0.7839	g_loss: 3.0450
Epoch [19/	20]	d_loss: 0.9493	g_loss: 2.9600
Epoch [19/	20]	d_loss: 0.8853	g_loss: 1.4898

Epoch [19/	20]	d_loss: 0.9659	g_loss: 1.4864
Epoch [19/	20]	d_loss: 0.6830	g_loss: 2.5309
Epoch [19/	20]	d_loss: 0.9917	g_loss: 2.5348
Epoch [19/	20]	d_loss: 1.4953	g_loss: 1.9250
Epoch [19/	20]	d_loss: 0.4410	g_loss: 2.9916
Epoch [19/	20]	d_loss: 0.5552	g_loss: 2.8080
Epoch [19/	20]	d_loss: 0.6311	g_loss: 1.8596
Epoch [19/	20]	d_loss: 0.6951	g_loss: 1.2085
Epoch [19/	20]	d_loss: 0.6199	g_loss: 1.3496
Epoch [19/	20]	d_loss: 0.6987	g_loss: 2.5058
Epoch [19/	20]	d_loss: 0.7674	g_loss: 3.3816
Epoch [19/	20]	d_loss: 0.6044	g_loss: 2.0638
Epoch [19/	20]	d_loss: 0.6181	g_loss: 3.1093
Epoch [19/	20]	d_loss: 0.7304	g_loss: 2.0611
Epoch [19/	20]	d_loss: 0.5230	g_loss: 3.5598
Epoch [19/	20]	d_loss: 0.6729	g_loss: 2.2826
Epoch [19/	20]	d_loss: 0.6523	g_loss: 2.9797
Epoch [19/	20]	d_loss: 0.6964	g_loss: 1.0485
Epoch [19/	20]	d_loss: 0.9815	g_loss: 1.7044
Epoch [19/	20]	d_loss: 0.4850	g_loss: 3.0402
Epoch [19/	20]	d_loss: 0.8843	g_loss: 3.0263
Epoch [19/	20]	d_loss: 0.6680	g_loss: 1.6425
Epoch [19/	20]	d_loss: 0.6254	g_loss: 2.5503
Epoch [19/	20]	d_loss: 0.8843	g_loss: 2.9107
Epoch [19/	20]	d_loss: 0.5059	g_loss: 2.3863
Epoch [19/	20]	d_loss: 0.7862	g_loss: 2.0949
Epoch [19/	20]	d_loss: 0.8642	g_loss: 1.2420
Epoch [19/	20]	d_loss: 0.5017	g_loss: 2.2498
Epoch [19/	20]	d_loss: 0.9011	g_loss: 2.4869
Epoch [19/	20]	d_loss: 0.7912	g_loss: 3.2564
Epoch [19/	20]	d_loss: 0.9036	g_loss: 2.3072
Epoch [19/	20]	d_loss: 0.6537	g_loss: 2.4892
Epoch [19/	20]	d_loss: 0.9856	g_loss: 1.8230
Epoch [19/	20]	d_loss: 0.6974	g_loss: 3.5683
Epoch [19/	20]	d_loss: 0.8720	g_loss: 1.7102
Epoch [19/	20]	d_loss: 0.5744	g_loss: 4.1938
Epoch [19/	20]	d_loss: 0.7319	g_loss: 2.0310
Epoch [19/	20]	d_loss: 0.6079	g_loss: 3.2692
Epoch [19/	20]	d_loss: 0.6811	g_loss: 1.4666
Epoch [19/	20]	d_loss: 0.9788	g_loss: 3.3136
Epoch [19/	20]	d_loss: 0.8530	g_loss: 2.5627
Epoch [19/	20]	d_loss: 0.6760	g_loss: 1.1650
Epoch [19/	20]	d_loss: 0.6712	g_loss: 2.0366
Epoch [19/	20]	d_loss: 0.8386	g_loss: 3.1648
Epoch [19/	20]	d_loss: 0.6143	g_loss: 1.8054
Epoch [19/	20]	d_loss: 0.7175	g_loss: 1.5347
Epoch [19/	20]	d_loss: 0.7970	g_loss: 1.2423
Epoch [19/	20]	d_loss: 0.5639	g_loss: 1.9605

Epoch [19/	20]	d_loss: 0.9214	g_loss: 1.6524
Epoch [19/	20]	d_loss: 0.5339	g_loss: 2.6060
Epoch [19/	20]	d_loss: 0.6773	g_loss: 2.3793
Epoch [19/	20]	d_loss: 1.0604	g_loss: 2.6288
Epoch [19/	20]	d_loss: 0.5649	g_loss: 2.2232
Epoch [19/	20]	d_loss: 0.5027	g_loss: 2.1210
Epoch [20/	20]	d_loss: 0.7218	g_loss: 2.3684
Epoch [20/	20]	d_loss: 1.1098	g_loss: 2.8287
Epoch [20/	20]	d_loss: 0.5236	g_loss: 2.5820
Epoch [20/	20]	d_loss: 0.4824	g_loss: 2.2719
Epoch [20/	20]	d_loss: 1.1892	g_loss: 1.8896
Epoch [20/	20]	d_loss: 1.6209	g_loss: 0.6663
Epoch [20/	20]	d_loss: 0.8145	g_loss: 3.1186
Epoch [20/	20]	d_loss: 0.6474	g_loss: 1.9422
Epoch [20/	20]	d_loss: 0.5925	g_loss: 2.1051
Epoch [20/	20]	d_loss: 1.0092	g_loss: 1.1114
Epoch [20/	20]	d_loss: 0.6464	g_loss: 4.2825
Epoch [20/	20]	d_loss: 0.5464	g_loss: 2.0075
Epoch [20/	20]	d_loss: 0.6921	g_loss: 2.9085
Epoch [20/	20]	d_loss: 1.1326	g_loss: 2.5260
Epoch [20/	20]	d_loss: 0.7264	g_loss: 2.0625
Epoch [20/	20]	d_loss: 0.4747	g_loss: 3.3205
Epoch [20/	20]	d_loss: 0.8937	g_loss: 1.9346
Epoch [20/	20]	d_loss: 0.7077	g_loss: 2.2547
Epoch [20/	20]	d_loss: 0.4992	g_loss: 3.5804
Epoch [20/	20]	d_loss: 0.6453	g_loss: 2.9467
Epoch [20/	20]	d_loss: 0.6017	g_loss: 3.2960
Epoch [20/	20]	d_loss: 0.4938	g_loss: 2.2505
Epoch [20/	20]	d_loss: 1.0161	g_loss: 2.1228
Epoch [20/	20]	d_loss: 0.8263	g_loss: 2.2612
Epoch [20/	20]	d_loss: 1.2367	g_loss: 2.3257
Epoch [20/	20]	d_loss: 1.5403	g_loss: 2.5413
Epoch [20/	20]	d_loss: 0.6304	g_loss: 1.1448
Epoch [20/	20]	d_loss: 0.7135	g_loss: 2.2574
Epoch [20/	20]	d_loss: 0.5186	g_loss: 2.7045
Epoch [20/	20]	d_loss: 0.8641	g_loss: 1.6471
Epoch [20/	20]	d_loss: 0.7141	g_loss: 2.2868
Epoch [20/	20]	d_loss: 0.6510	g_loss: 1.2789
Epoch [20/	20]	d_loss: 1.0150	g_loss: 1.8404
Epoch [20/	20]	d_loss: 1.3549	g_loss: 3.7053
Epoch [20/	20]	d_loss: 0.5677	g_loss: 2.0687
Epoch [20/	20]	d_loss: 0.5162	g_loss: 2.8573
Epoch [20/	20]	d_loss: 0.6188	g_loss: 2.1754
Epoch [20/	20]	d_loss: 0.8311	g_loss: 2.6876
Epoch [20/	20]	d_loss: 0.5172	g_loss: 2.0483
Epoch [20/	20]	d_loss: 1.2065	g_loss: 2.5250
Epoch [20/	20]	d_loss: 0.7892	g_loss: 2.3359
Epoch [20/	20]	d_loss: 0.7492	g_loss: 2.1295

```

Epoch [ 20/ 20] | d_loss: 0.5869 | g_loss: 2.5117
Epoch [ 20/ 20] | d_loss: 1.3604 | g_loss: 2.8163
Epoch [ 20/ 20] | d_loss: 0.8007 | g_loss: 1.4255
Epoch [ 20/ 20] | d_loss: 0.8116 | g_loss: 2.4831
Epoch [ 20/ 20] | d_loss: 0.8342 | g_loss: 2.8697
Epoch [ 20/ 20] | d_loss: 0.6238 | g_loss: 3.8051
Epoch [ 20/ 20] | d_loss: 0.8757 | g_loss: 2.1380
Epoch [ 20/ 20] | d_loss: 0.8475 | g_loss: 2.8795
Epoch [ 20/ 20] | d_loss: 0.6528 | g_loss: 2.4820
Epoch [ 20/ 20] | d_loss: 0.6074 | g_loss: 1.7928
Epoch [ 20/ 20] | d_loss: 0.6357 | g_loss: 1.6599
Epoch [ 20/ 20] | d_loss: 0.6990 | g_loss: 2.9249
Epoch [ 20/ 20] | d_loss: 0.5469 | g_loss: 1.3986
Epoch [ 20/ 20] | d_loss: 0.9948 | g_loss: 2.2753
Epoch [ 20/ 20] | d_loss: 0.7320 | g_loss: 1.8144

```

2.9 Training loss

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

```

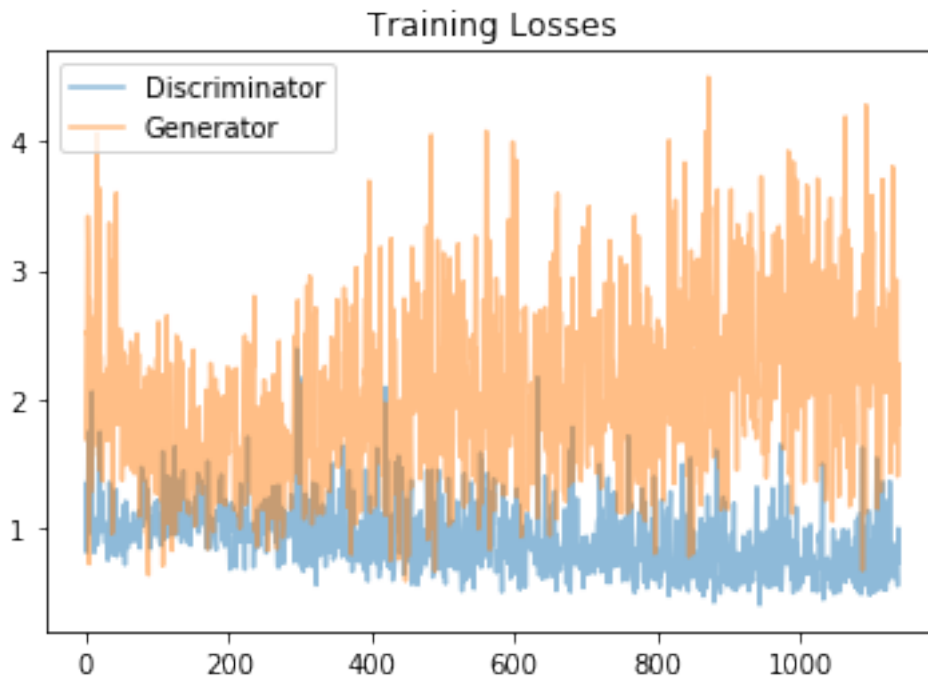
In [21]: fig, ax = plt.subplots()
         losses = np.array(losses)
         plt.plot(losses.T[0], label='Discriminator', alpha=0.5)
         plt.plot(losses.T[1], label='Generator', alpha=0.5)
         plt.title("Training Losses")
         plt.legend()

```

```

Out[21]: <matplotlib.legend.Legend at 0x7fdd3c16deb8>

```



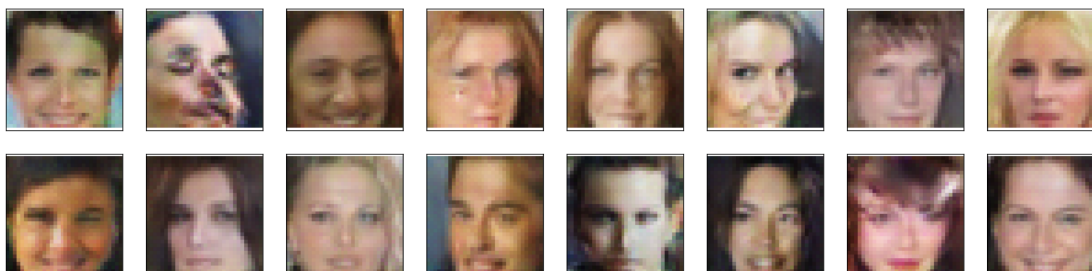
2.10 Generator samples from training

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

```
In [22]: # 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 [23]: # Load samples from generator, taken while training
with open('train_samples.pkl', 'rb') as f:
    samples = pickle.load(f)

In [24]: _ = 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 "dlnn_face_generation.ipynb" and save it as a HTML file under "File" -> "Download as". Include the "problem_unittests.py" files in your submission.