dlnd_face_generation

February 23, 2020

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 [1]: data_dir = 'processed_celeba_small/'

        """
        DON'T MODIFY ANYTHING IN THIS CELL
        """
        import pickle as pkl
        import matplotlib.pyplot as plt
```

```
import numpy as np
import problem_unittests as tests
#import helper

%matplotlib inline
```

1.1 Visualize the CelebA Data

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

1.1.1 Pre-process and Load the Data

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

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

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

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

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

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

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

            # resize and normalize the images
```

```
    my_transformation = transforms.Compose([
                    transforms.Resize(image_size),
                    transforms.ToTensor()
                ])
    # define dataset unig ImageFolder
    my_dataset = datasets.ImageFolder(data_dir,
                                      transform = my_transformation)

    # create and return DataLoader
    data_loader = torch.utils.data.DataLoader(dataset = my_dataset,
                                              batch_size = batch_size,
                                              shuffle = True)

    return data_loader
    #return None
```

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 [30]: # Define function hyperparameters
         batch_size = 64
         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)
```

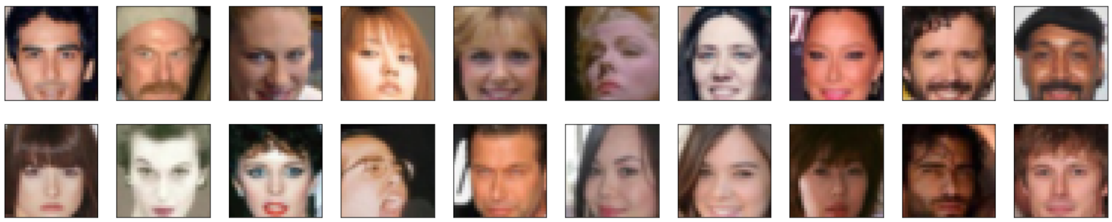
Next, you can view some images! You should seen square images of somewhat-centered faces.

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

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

        """
        DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
        """
        # obtain one batch of training images
        dataiter = iter(celeba_train_loader)
        images, _ = dataiter.next() # _ for no labels
```

```python
# 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.)

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

            min, max = feature_range
            x = x * (max - min) + min
            return x
```

```python
In [9]: """
        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(0.9137)
```

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 [10]:
```
import torch.nn as nn
import torch.nn.functional as F

# Based on https://github.com/udacity/deep-learning-v2-pytorch/tree/master/cycle-gan
# 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, bia

    layers.append(conv_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
        # 32x32 input
        self.conv1 = conv(3, conv_dim, 4, batch_norm=False) # first layer, no batch_nor
        # 16x16 out
        self.conv2 = conv(conv_dim, conv_dim*2, 4)
```

```
        # 8x8 out
        self.conv3 = conv(conv_dim*2, conv_dim*4, 4)
        # 4x4 out

        # final, fully-connected layer
        self.fc = nn.Linear(conv_dim*4*4*4, 1) # depth=conv_dim*4, image=4*4

        # dropout layer
        self.dropout = nn.Dropout(0.3)

    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

        # all hidden layers + leaky relu activation
        # applying a dropout layer in-between each of linear layers to ensure
        # that the network is likely to train each node evenly
        x = F.leaky_relu(self.conv1(x), 0.2)
        x = self.dropout(x)
        x = F.leaky_relu(self.conv2(x), 0.2)
        x = self.dropout(x)
        x = F.leaky_relu(self.conv3(x), 0.2)
        x = self.dropout(x)

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

        # final output layer
        x = self.fc(x)
        return x


"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""
tests.test_discriminator(Discriminator)
```

```
Tests Passed
```

2.2 Generator

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

Exercise: Complete the Generator class

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

In [12]:
```
# helper deconv function
def deconv(in_channels, out_channels, kernel_size, stride=2, padding=1, batch_norm=True
    """Creates a transposed-convolutional layer, with optional batch normalization.
    """
    # create a sequence of transpose + optional batch norm layers
    layers = []
    transpose_conv_layer = nn.ConvTranspose2d(in_channels, out_channels,
                                              kernel_size, stride, padding, bias=False)
    # append transpose convolutional layer
    layers.append(transpose_conv_layer)

    if batch_norm:
        # append batchnorm layer
        layers.append(nn.BatchNorm2d(out_channels))

    return nn.Sequential(*layers)
```

In [13]:
```
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

        # first, fully-connected layer
        self.fc = nn.Linear(z_size, conv_dim*4*4*4)

        # transpose conv layers
        self.t_conv1 = deconv(conv_dim*4, conv_dim*2, 4)
        self.t_conv2 = deconv(conv_dim*2, conv_dim, 4)
        self.t_conv3 = deconv(conv_dim, 3, 4, batch_norm=False)

    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
            x = self.fc(x) # fc(x)--> x here is from a forward function. It's a z-vector
            x = x.view(-1, self.conv_dim*4, 4, 4) # (batch_size, depth, 4, 4)

            # hidden transpose conv layers + relu
            x = F.relu(self.t_conv1(x))
            x = F.relu(self.t_conv2(x))

            # last layer + tanh activation
            x = self.t_conv3(x)
            x = F.tanh(x)

            return x

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

```
Tests Passed
```

2.3 Initialize the weights of your networks

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

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

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

Exercise: Complete the weight initialization function

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

```
In [14]: from torch.nn import init
         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
    init_gain=0.02
    if hasattr(m, 'weight') and (classname.find('Conv') != -1 or classname.find('Linear
        init.normal_(m.weight.data, 0.0, init_gain)
        if hasattr(m, 'bias') and m.bias is not None:
            init.constant_(m.bias.data, 0.0)
    elif classname.find('BatchNorm2d') != -1:  # BatchNorm Layer's weight is not a matr
        init.normal_(m.weight.data, 1.0, init_gain)
        init.constant_(m.bias.data, 0.0)
```

2.4 Build complete network

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

```
In [15]: """
         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 [16]: # 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): Sequential(
    (0): Conv2d(3, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  )
  (conv2): Sequential(
    (0): Conv2d(32, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (conv3): Sequential(
    (0): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (fc): Linear(in_features=2048, out_features=1, bias=True)
  (dropout): Dropout(p=0.3)
)

Generator(
  (fc): Linear(in_features=100, out_features=2048, bias=True)
  (t_conv1): Sequential(
    (0): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (t_conv2): Sequential(
    (0): ConvTranspose2d(64, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (t_conv3): Sequential(
    (0): ConvTranspose2d(32, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  )
)
```

2.4.1 Training on GPU

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

Are moved to GPU, where appropriate.

In [17]:
```
"""
DON'T MODIFY ANYTHING IN THIS CELL
"""
import torch

# Check for a GPU
```

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

```
Training on GPU!
```

2.5 Discriminator and Generator Losses

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

2.5.1 Discriminator Losses

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

2.5.2 Generator Loss

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

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

```
In [22]: def real_loss(D_out, smooth=False):
             '''Calculates how close discriminator outputs are to being real.
                param, D_out: discriminator logits
                return: real loss'''
             batch_size = D_out.size(0)
             # label smoothing
             if smooth:
                 # smooth, real labels = 0.9
                 labels = torch.ones(batch_size)*0.9
             else:
                 labels = torch.ones(batch_size) # real labels = 1
             # move labels to GPU if available
             if train_on_gpu:
                 labels = labels.cuda()
             # binary cross entropy with logits loss
             criterion = nn.BCEWithLogitsLoss()
             # calculate loss
             loss = criterion(D_out.squeeze(), labels)
             return loss
```

```python
def fake_loss(D_out):
    '''Calculates how close discriminator outputs are to being fake.
       param, D_out: discriminator logits
       return: fake loss'''
    batch_size = D_out.size(0)
    labels = torch.zeros(batch_size) # fake labels = 0
    if train_on_gpu:
        labels = labels.cuda()
    criterion = nn.BCEWithLogitsLoss()
    # calculate loss
    loss = criterion(D_out.squeeze(), labels)
    return loss
```

2.6 Optimizers

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

```python
In [23]: import torch.optim as optim

         # params
         lr=0.0002
         beta1=0.5
         beta2=0.999

         # Create optimizers for the discriminator D and generator G
         d_optimizer = optim.Adam(D.parameters(), lr, [beta1, beta2])
         g_optimizer = optim.Adam(G.parameters(), lr, [beta1, beta2])
```

2.7 Training

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

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

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

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

In [24]:
```
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

            d_optimizer.zero_grad()

            if train_on_gpu:
                real_images = real_images.cuda()

            D_real = D(real_images)
            d_real_loss = real_loss(D_real)
```

```python
# no smoothing as it was found to work a little better wothout smooting

# 2. Train the generator with an adversarial loss

# Generate fake images
z = np.random.uniform(-1, 1, size=(batch_size, z_size))
z = torch.from_numpy(z).float()
# move x to GPU, if available
if train_on_gpu:
    z = z.cuda()
fake_images = G(z)

# Compute the discriminator losses on fake images
D_fake = D(fake_images)
d_fake_loss = fake_loss(D_fake)

# add up loss and perform backprop
d_loss = d_real_loss + d_fake_loss
d_loss.backward()
d_optimizer.step()


# =========================================
#            TRAIN THE GENERATOR
# =========================================
g_optimizer.zero_grad()

# 1. Train with fake images and flipped labels

# Generate fake images
z = np.random.uniform(-1, 1, size=(batch_size, z_size))
z = torch.from_numpy(z).float()
if train_on_gpu:
    z = z.cuda()
fake_images = G(z)

# Compute the discriminator losses on fake images
# using flipped labels!
D_fake = D(fake_images)
g_loss = real_loss(D_fake) # use real loss to flip labels

# perform backprop
g_loss.backward()
g_optimizer.step()

# ===============================================
#               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: {:6.4f} | g_loss: {:6.4f}'.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:
            pkl.dump(samples, f)

        # finally return losses
        return losses
```

Set your number of training epochs and train your GAN!

In [25]:
```
# 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: 1.4700 | g_loss: 0.8880
Epoch [    1/   10] | d_loss: 0.4251 | g_loss: 2.4885
Epoch [    1/   10] | d_loss: 0.1570 | g_loss: 4.3911
Epoch [    1/   10] | d_loss: 0.2400 | g_loss: 4.7571
Epoch [    1/   10] | d_loss: 0.7249 | g_loss: 6.4529
Epoch [    1/   10] | d_loss: 0.5930 | g_loss: 4.7274
Epoch [    1/   10] | d_loss: 0.3949 | g_loss: 3.0627
Epoch [    1/   10] | d_loss: 0.7211 | g_loss: 2.1344
Epoch [    1/   10] | d_loss: 0.6956 | g_loss: 2.9010
Epoch [    1/   10] | d_loss: 0.6042 | g_loss: 2.7611
Epoch [    1/   10] | d_loss: 0.6038 | g_loss: 2.3712
```

```
Epoch [    1/   10] | d_loss: 0.7102 | g_loss: 2.0412
Epoch [    1/   10] | d_loss: 0.8699 | g_loss: 2.5723
Epoch [    1/   10] | d_loss: 1.3123 | g_loss: 1.0970
Epoch [    1/   10] | d_loss: 0.6211 | g_loss: 1.8869
Epoch [    1/   10] | d_loss: 0.9560 | g_loss: 1.3247
Epoch [    1/   10] | d_loss: 0.8523 | g_loss: 1.6930
Epoch [    1/   10] | d_loss: 0.9443 | g_loss: 1.3997
Epoch [    1/   10] | d_loss: 0.8191 | g_loss: 1.4714
Epoch [    1/   10] | d_loss: 1.0086 | g_loss: 1.8679
Epoch [    1/   10] | d_loss: 1.1239 | g_loss: 1.4826
Epoch [    1/   10] | d_loss: 1.0754 | g_loss: 1.1064
Epoch [    1/   10] | d_loss: 1.1550 | g_loss: 1.5362
Epoch [    1/   10] | d_loss: 0.8660 | g_loss: 1.2419
Epoch [    1/   10] | d_loss: 1.1333 | g_loss: 1.8620
Epoch [    1/   10] | d_loss: 0.9600 | g_loss: 1.4308
Epoch [    1/   10] | d_loss: 1.1397 | g_loss: 1.3881
Epoch [    1/   10] | d_loss: 1.2638 | g_loss: 1.3908
Epoch [    1/   10] | d_loss: 1.0854 | g_loss: 1.0093
Epoch [    2/   10] | d_loss: 1.3366 | g_loss: 0.8266
Epoch [    2/   10] | d_loss: 0.9802 | g_loss: 0.8689
Epoch [    2/   10] | d_loss: 1.0359 | g_loss: 1.4364
Epoch [    2/   10] | d_loss: 1.2820 | g_loss: 1.0301
Epoch [    2/   10] | d_loss: 1.0509 | g_loss: 1.5146
Epoch [    2/   10] | d_loss: 1.3702 | g_loss: 1.4672
Epoch [    2/   10] | d_loss: 0.9660 | g_loss: 1.1944
Epoch [    2/   10] | d_loss: 1.1003 | g_loss: 1.3726
Epoch [    2/   10] | d_loss: 1.2946 | g_loss: 1.2498
Epoch [    2/   10] | d_loss: 1.2333 | g_loss: 1.2649
Epoch [    2/   10] | d_loss: 0.9968 | g_loss: 1.0619
Epoch [    2/   10] | d_loss: 1.2614 | g_loss: 1.4217
Epoch [    2/   10] | d_loss: 1.3446 | g_loss: 0.9185
Epoch [    2/   10] | d_loss: 1.2176 | g_loss: 1.1696
Epoch [    2/   10] | d_loss: 1.2434 | g_loss: 1.2470
Epoch [    2/   10] | d_loss: 1.1834 | g_loss: 0.8979
Epoch [    2/   10] | d_loss: 1.2100 | g_loss: 1.3319
Epoch [    2/   10] | d_loss: 1.1607 | g_loss: 0.9028
Epoch [    2/   10] | d_loss: 1.3429 | g_loss: 0.7372
Epoch [    2/   10] | d_loss: 1.0932 | g_loss: 1.1218
Epoch [    2/   10] | d_loss: 1.0377 | g_loss: 1.5378
Epoch [    2/   10] | d_loss: 1.0113 | g_loss: 1.4318
Epoch [    2/   10] | d_loss: 1.3242 | g_loss: 1.0005
Epoch [    2/   10] | d_loss: 1.2045 | g_loss: 0.9995
Epoch [    2/   10] | d_loss: 1.2905 | g_loss: 1.2346
Epoch [    2/   10] | d_loss: 1.3069 | g_loss: 1.2506
Epoch [    2/   10] | d_loss: 1.4221 | g_loss: 1.0381
Epoch [    2/   10] | d_loss: 1.4721 | g_loss: 0.9996
Epoch [    2/   10] | d_loss: 1.2811 | g_loss: 1.2823
Epoch [    3/   10] | d_loss: 1.1461 | g_loss: 0.7340
```

```
Epoch [    3/   10] | d_loss: 1.1866 | g_loss: 1.0748
Epoch [    3/   10] | d_loss: 1.2323 | g_loss: 0.9138
Epoch [    3/   10] | d_loss: 1.3460 | g_loss: 1.0880
Epoch [    3/   10] | d_loss: 1.0476 | g_loss: 1.3735
Epoch [    3/   10] | d_loss: 1.0570 | g_loss: 1.3292
Epoch [    3/   10] | d_loss: 1.3005 | g_loss: 0.9895
Epoch [    3/   10] | d_loss: 1.2052 | g_loss: 0.8066
Epoch [    3/   10] | d_loss: 1.3367 | g_loss: 1.7338
Epoch [    3/   10] | d_loss: 1.1379 | g_loss: 0.9770
Epoch [    3/   10] | d_loss: 1.0162 | g_loss: 1.4191
Epoch [    3/   10] | d_loss: 1.2198 | g_loss: 0.6791
Epoch [    3/   10] | d_loss: 1.1604 | g_loss: 0.9042
Epoch [    3/   10] | d_loss: 1.3923 | g_loss: 1.1504
Epoch [    3/   10] | d_loss: 1.1654 | g_loss: 0.9348
Epoch [    3/   10] | d_loss: 1.1159 | g_loss: 1.1775
Epoch [    3/   10] | d_loss: 1.1391 | g_loss: 1.2324
Epoch [    3/   10] | d_loss: 1.2586 | g_loss: 1.0634
Epoch [    3/   10] | d_loss: 1.2252 | g_loss: 1.1625
Epoch [    3/   10] | d_loss: 1.2474 | g_loss: 0.9151
Epoch [    3/   10] | d_loss: 1.0826 | g_loss: 1.3529
Epoch [    3/   10] | d_loss: 1.3378 | g_loss: 0.9827
Epoch [    3/   10] | d_loss: 1.1801 | g_loss: 0.7039
Epoch [    3/   10] | d_loss: 1.0839 | g_loss: 1.2777
Epoch [    3/   10] | d_loss: 1.3095 | g_loss: 1.0614
Epoch [    3/   10] | d_loss: 1.4357 | g_loss: 0.8241
Epoch [    3/   10] | d_loss: 1.1819 | g_loss: 0.8880
Epoch [    3/   10] | d_loss: 1.1471 | g_loss: 0.9062
Epoch [    3/   10] | d_loss: 1.1793 | g_loss: 0.6497
Epoch [    4/   10] | d_loss: 1.2522 | g_loss: 1.1134
Epoch [    4/   10] | d_loss: 1.1459 | g_loss: 1.1406
Epoch [    4/   10] | d_loss: 1.3981 | g_loss: 1.0779
Epoch [    4/   10] | d_loss: 1.1669 | g_loss: 0.7122
Epoch [    4/   10] | d_loss: 1.3491 | g_loss: 0.8014
Epoch [    4/   10] | d_loss: 1.3364 | g_loss: 0.9730
Epoch [    4/   10] | d_loss: 1.1546 | g_loss: 1.1656
Epoch [    4/   10] | d_loss: 1.5158 | g_loss: 0.8450
Epoch [    4/   10] | d_loss: 1.3611 | g_loss: 1.0797
Epoch [    4/   10] | d_loss: 1.3973 | g_loss: 0.8687
Epoch [    4/   10] | d_loss: 0.9968 | g_loss: 1.3245
Epoch [    4/   10] | d_loss: 1.3149 | g_loss: 1.4523
Epoch [    4/   10] | d_loss: 1.2302 | g_loss: 0.8995
Epoch [    4/   10] | d_loss: 1.3023 | g_loss: 0.9873
Epoch [    4/   10] | d_loss: 1.1481 | g_loss: 1.3128
Epoch [    4/   10] | d_loss: 1.0703 | g_loss: 0.9446
Epoch [    4/   10] | d_loss: 1.3870 | g_loss: 0.8813
Epoch [    4/   10] | d_loss: 1.4876 | g_loss: 0.9097
Epoch [    4/   10] | d_loss: 1.3338 | g_loss: 0.7912
Epoch [    4/   10] | d_loss: 0.9730 | g_loss: 1.0509
```

```
Epoch [    4/   10] | d_loss: 1.2065 | g_loss: 0.9431
Epoch [    4/   10] | d_loss: 1.1987 | g_loss: 0.9731
Epoch [    4/   10] | d_loss: 1.1137 | g_loss: 0.9643
Epoch [    4/   10] | d_loss: 1.0831 | g_loss: 1.0460
Epoch [    4/   10] | d_loss: 1.3130 | g_loss: 1.2180
Epoch [    4/   10] | d_loss: 0.9991 | g_loss: 1.0101
Epoch [    4/   10] | d_loss: 1.2448 | g_loss: 1.1507
Epoch [    4/   10] | d_loss: 1.1648 | g_loss: 1.1985
Epoch [    4/   10] | d_loss: 1.3436 | g_loss: 0.9330
Epoch [    5/   10] | d_loss: 1.1200 | g_loss: 0.9460
Epoch [    5/   10] | d_loss: 1.3623 | g_loss: 0.9731
Epoch [    5/   10] | d_loss: 1.0899 | g_loss: 1.0052
Epoch [    5/   10] | d_loss: 1.1526 | g_loss: 1.1232
Epoch [    5/   10] | d_loss: 1.1792 | g_loss: 0.9877
Epoch [    5/   10] | d_loss: 1.1478 | g_loss: 0.6008
Epoch [    5/   10] | d_loss: 1.2038 | g_loss: 1.0866
Epoch [    5/   10] | d_loss: 1.0010 | g_loss: 1.1985
Epoch [    5/   10] | d_loss: 1.2427 | g_loss: 0.9178
Epoch [    5/   10] | d_loss: 1.0630 | g_loss: 0.9205
Epoch [    5/   10] | d_loss: 1.2579 | g_loss: 1.3579
Epoch [    5/   10] | d_loss: 1.2985 | g_loss: 1.1281
Epoch [    5/   10] | d_loss: 1.2670 | g_loss: 0.8779
Epoch [    5/   10] | d_loss: 1.1239 | g_loss: 1.0754
Epoch [    5/   10] | d_loss: 1.2922 | g_loss: 0.8742
Epoch [    5/   10] | d_loss: 1.2634 | g_loss: 0.9878
Epoch [    5/   10] | d_loss: 1.2984 | g_loss: 0.9878
Epoch [    5/   10] | d_loss: 1.1937 | g_loss: 0.8460
Epoch [    5/   10] | d_loss: 1.1990 | g_loss: 0.9645
Epoch [    5/   10] | d_loss: 1.4178 | g_loss: 0.8617
Epoch [    5/   10] | d_loss: 1.1960 | g_loss: 1.1743
Epoch [    5/   10] | d_loss: 1.1500 | g_loss: 1.0782
Epoch [    5/   10] | d_loss: 1.2434 | g_loss: 1.0145
Epoch [    5/   10] | d_loss: 1.1373 | g_loss: 1.0369
Epoch [    5/   10] | d_loss: 1.3405 | g_loss: 0.9337
Epoch [    5/   10] | d_loss: 1.3684 | g_loss: 1.0543
Epoch [    5/   10] | d_loss: 1.3464 | g_loss: 0.8790
Epoch [    5/   10] | d_loss: 1.1784 | g_loss: 0.9263
Epoch [    5/   10] | d_loss: 1.3026 | g_loss: 1.3046
Epoch [    6/   10] | d_loss: 1.3113 | g_loss: 0.8179
Epoch [    6/   10] | d_loss: 1.1855 | g_loss: 0.9334
Epoch [    6/   10] | d_loss: 1.1229 | g_loss: 0.9656
Epoch [    6/   10] | d_loss: 1.2729 | g_loss: 1.1526
Epoch [    6/   10] | d_loss: 1.2367 | g_loss: 0.8374
Epoch [    6/   10] | d_loss: 1.2956 | g_loss: 1.1615
Epoch [    6/   10] | d_loss: 1.1718 | g_loss: 0.8399
Epoch [    6/   10] | d_loss: 1.1839 | g_loss: 0.9898
Epoch [    6/   10] | d_loss: 1.1582 | g_loss: 1.2594
Epoch [    6/   10] | d_loss: 1.2434 | g_loss: 1.0625
```

```
Epoch [    6/   10] | d_loss: 1.3493 | g_loss: 1.1043
Epoch [    6/   10] | d_loss: 1.2628 | g_loss: 0.9166
Epoch [    6/   10] | d_loss: 1.1387 | g_loss: 1.1104
Epoch [    6/   10] | d_loss: 1.3852 | g_loss: 0.9558
Epoch [    6/   10] | d_loss: 1.4288 | g_loss: 0.9298
Epoch [    6/   10] | d_loss: 1.2232 | g_loss: 1.0014
Epoch [    6/   10] | d_loss: 1.4434 | g_loss: 1.0584
Epoch [    6/   10] | d_loss: 1.1488 | g_loss: 0.9304
Epoch [    6/   10] | d_loss: 1.3384 | g_loss: 0.8666
Epoch [    6/   10] | d_loss: 0.9801 | g_loss: 1.2457
Epoch [    6/   10] | d_loss: 1.2241 | g_loss: 1.1045
Epoch [    6/   10] | d_loss: 1.2128 | g_loss: 0.7986
Epoch [    6/   10] | d_loss: 1.1309 | g_loss: 0.9417
Epoch [    6/   10] | d_loss: 1.0522 | g_loss: 1.1458
Epoch [    6/   10] | d_loss: 1.2330 | g_loss: 0.9512
Epoch [    6/   10] | d_loss: 1.0651 | g_loss: 1.2413
Epoch [    6/   10] | d_loss: 1.2327 | g_loss: 0.9925
Epoch [    6/   10] | d_loss: 1.1042 | g_loss: 1.0987
Epoch [    6/   10] | d_loss: 1.4625 | g_loss: 0.8554
Epoch [    7/   10] | d_loss: 1.1553 | g_loss: 1.0541
Epoch [    7/   10] | d_loss: 1.2941 | g_loss: 1.1630
Epoch [    7/   10] | d_loss: 1.1930 | g_loss: 1.0722
Epoch [    7/   10] | d_loss: 1.3547 | g_loss: 1.3097
Epoch [    7/   10] | d_loss: 1.4457 | g_loss: 1.0158
Epoch [    7/   10] | d_loss: 1.4251 | g_loss: 1.0158
Epoch [    7/   10] | d_loss: 1.1293 | g_loss: 1.2996
Epoch [    7/   10] | d_loss: 1.2557 | g_loss: 1.0512
Epoch [    7/   10] | d_loss: 1.3712 | g_loss: 0.9624
Epoch [    7/   10] | d_loss: 1.1583 | g_loss: 0.7633
Epoch [    7/   10] | d_loss: 1.1256 | g_loss: 0.7830
Epoch [    7/   10] | d_loss: 1.1962 | g_loss: 0.9581
Epoch [    7/   10] | d_loss: 1.2114 | g_loss: 0.9903
Epoch [    7/   10] | d_loss: 1.1911 | g_loss: 1.0938
Epoch [    7/   10] | d_loss: 1.3808 | g_loss: 0.8572
Epoch [    7/   10] | d_loss: 1.1458 | g_loss: 1.1487
Epoch [    7/   10] | d_loss: 1.2880 | g_loss: 0.9261
Epoch [    7/   10] | d_loss: 1.3385 | g_loss: 0.9878
Epoch [    7/   10] | d_loss: 1.4816 | g_loss: 0.9535
Epoch [    7/   10] | d_loss: 1.2055 | g_loss: 1.1806
Epoch [    7/   10] | d_loss: 1.3698 | g_loss: 0.9677
Epoch [    7/   10] | d_loss: 1.0888 | g_loss: 1.1377
Epoch [    7/   10] | d_loss: 1.3311 | g_loss: 0.7654
Epoch [    7/   10] | d_loss: 1.2916 | g_loss: 1.0941
Epoch [    7/   10] | d_loss: 1.0593 | g_loss: 0.9455
Epoch [    7/   10] | d_loss: 1.3259 | g_loss: 1.0420
Epoch [    7/   10] | d_loss: 1.3447 | g_loss: 0.8980
Epoch [    7/   10] | d_loss: 1.0623 | g_loss: 0.8661
Epoch [    7/   10] | d_loss: 1.3554 | g_loss: 0.7139
```

```
Epoch [    8/   10] | d_loss: 1.3771 | g_loss: 0.9959
Epoch [    8/   10] | d_loss: 1.4271 | g_loss: 0.6083
Epoch [    8/   10] | d_loss: 1.2317 | g_loss: 1.1492
Epoch [    8/   10] | d_loss: 1.4580 | g_loss: 0.8989
Epoch [    8/   10] | d_loss: 1.3450 | g_loss: 0.9139
Epoch [    8/   10] | d_loss: 1.2489 | g_loss: 1.0065
Epoch [    8/   10] | d_loss: 1.2666 | g_loss: 0.8847
Epoch [    8/   10] | d_loss: 1.3528 | g_loss: 0.9676
Epoch [    8/   10] | d_loss: 1.1229 | g_loss: 1.1373
Epoch [    8/   10] | d_loss: 1.3126 | g_loss: 0.8018
Epoch [    8/   10] | d_loss: 1.3030 | g_loss: 1.0511
Epoch [    8/   10] | d_loss: 1.3059 | g_loss: 0.8024
Epoch [    8/   10] | d_loss: 1.2333 | g_loss: 0.9223
Epoch [    8/   10] | d_loss: 1.1612 | g_loss: 1.2163
Epoch [    8/   10] | d_loss: 1.3063 | g_loss: 0.8269
Epoch [    8/   10] | d_loss: 1.1201 | g_loss: 1.0244
Epoch [    8/   10] | d_loss: 1.4444 | g_loss: 0.8099
Epoch [    8/   10] | d_loss: 1.2185 | g_loss: 0.9337
Epoch [    8/   10] | d_loss: 1.1699 | g_loss: 0.9643
Epoch [    8/   10] | d_loss: 1.1815 | g_loss: 1.0284
Epoch [    8/   10] | d_loss: 1.3872 | g_loss: 0.8185
Epoch [    8/   10] | d_loss: 1.1327 | g_loss: 0.9891
Epoch [    8/   10] | d_loss: 1.3784 | g_loss: 0.8816
Epoch [    8/   10] | d_loss: 1.3321 | g_loss: 0.9770
Epoch [    8/   10] | d_loss: 1.2738 | g_loss: 0.9370
Epoch [    8/   10] | d_loss: 1.0663 | g_loss: 1.1150
Epoch [    8/   10] | d_loss: 1.2732 | g_loss: 0.9180
Epoch [    8/   10] | d_loss: 1.3261 | g_loss: 1.0478
Epoch [    8/   10] | d_loss: 1.1241 | g_loss: 0.8770
Epoch [    9/   10] | d_loss: 1.2698 | g_loss: 0.9613
Epoch [    9/   10] | d_loss: 1.2891 | g_loss: 1.1542
Epoch [    9/   10] | d_loss: 1.2510 | g_loss: 1.1476
Epoch [    9/   10] | d_loss: 1.1773 | g_loss: 0.8670
Epoch [    9/   10] | d_loss: 1.2472 | g_loss: 0.9761
Epoch [    9/   10] | d_loss: 1.1537 | g_loss: 0.8364
Epoch [    9/   10] | d_loss: 1.1720 | g_loss: 0.9785
Epoch [    9/   10] | d_loss: 1.2464 | g_loss: 1.0173
Epoch [    9/   10] | d_loss: 1.3715 | g_loss: 1.1436
Epoch [    9/   10] | d_loss: 1.3024 | g_loss: 0.8958
Epoch [    9/   10] | d_loss: 1.3261 | g_loss: 0.8753
Epoch [    9/   10] | d_loss: 1.2103 | g_loss: 0.9016
Epoch [    9/   10] | d_loss: 1.3909 | g_loss: 0.5502
Epoch [    9/   10] | d_loss: 1.3035 | g_loss: 0.9937
Epoch [    9/   10] | d_loss: 1.4184 | g_loss: 0.9198
Epoch [    9/   10] | d_loss: 1.4132 | g_loss: 1.0217
Epoch [    9/   10] | d_loss: 1.2735 | g_loss: 0.8842
Epoch [    9/   10] | d_loss: 1.5238 | g_loss: 0.8907
Epoch [    9/   10] | d_loss: 1.2574 | g_loss: 1.1718
```

```
Epoch [    9/   10] | d_loss: 1.7234 | g_loss: 0.9651
Epoch [    9/   10] | d_loss: 1.3466 | g_loss: 0.9404
Epoch [    9/   10] | d_loss: 1.3295 | g_loss: 0.9198
Epoch [    9/   10] | d_loss: 1.3145 | g_loss: 0.8945
Epoch [    9/   10] | d_loss: 1.3815 | g_loss: 0.9309
Epoch [    9/   10] | d_loss: 1.2922 | g_loss: 0.7477
Epoch [    9/   10] | d_loss: 1.2568 | g_loss: 0.6240
Epoch [    9/   10] | d_loss: 1.1769 | g_loss: 0.8698
Epoch [    9/   10] | d_loss: 1.4335 | g_loss: 0.6805
Epoch [    9/   10] | d_loss: 1.3504 | g_loss: 0.8911
Epoch [   10/   10] | d_loss: 1.1212 | g_loss: 0.9933
Epoch [   10/   10] | d_loss: 1.3929 | g_loss: 0.8499
Epoch [   10/   10] | d_loss: 1.2407 | g_loss: 0.9947
Epoch [   10/   10] | d_loss: 1.1119 | g_loss: 0.9207
Epoch [   10/   10] | d_loss: 1.3652 | g_loss: 0.9551
Epoch [   10/   10] | d_loss: 1.3789 | g_loss: 0.9373
Epoch [   10/   10] | d_loss: 1.2374 | g_loss: 0.9114
Epoch [   10/   10] | d_loss: 1.2864 | g_loss: 1.0930
Epoch [   10/   10] | d_loss: 1.6527 | g_loss: 0.9479
Epoch [   10/   10] | d_loss: 1.3960 | g_loss: 0.9701
Epoch [   10/   10] | d_loss: 1.3105 | g_loss: 0.9012
Epoch [   10/   10] | d_loss: 1.4606 | g_loss: 1.0054
Epoch [   10/   10] | d_loss: 1.4507 | g_loss: 0.8719
Epoch [   10/   10] | d_loss: 1.4056 | g_loss: 0.8449
Epoch [   10/   10] | d_loss: 1.3565 | g_loss: 0.9061
Epoch [   10/   10] | d_loss: 1.0628 | g_loss: 0.9575
Epoch [   10/   10] | d_loss: 1.4035 | g_loss: 1.0265
Epoch [   10/   10] | d_loss: 1.2747 | g_loss: 1.0855
Epoch [   10/   10] | d_loss: 1.0833 | g_loss: 0.9281
Epoch [   10/   10] | d_loss: 0.9872 | g_loss: 0.8838
Epoch [   10/   10] | d_loss: 0.9663 | g_loss: 1.2958
Epoch [   10/   10] | d_loss: 1.3694 | g_loss: 0.7770
Epoch [   10/   10] | d_loss: 1.2609 | g_loss: 0.8387
Epoch [   10/   10] | d_loss: 1.4186 | g_loss: 0.8994
Epoch [   10/   10] | d_loss: 1.2103 | g_loss: 1.2235
Epoch [   10/   10] | d_loss: 1.2129 | g_loss: 0.7963
Epoch [   10/   10] | d_loss: 1.4001 | g_loss: 0.9450
Epoch [   10/   10] | d_loss: 1.2546 | g_loss: 1.0183
Epoch [   10/   10] | d_loss: 1.5298 | g_loss: 0.6739
```

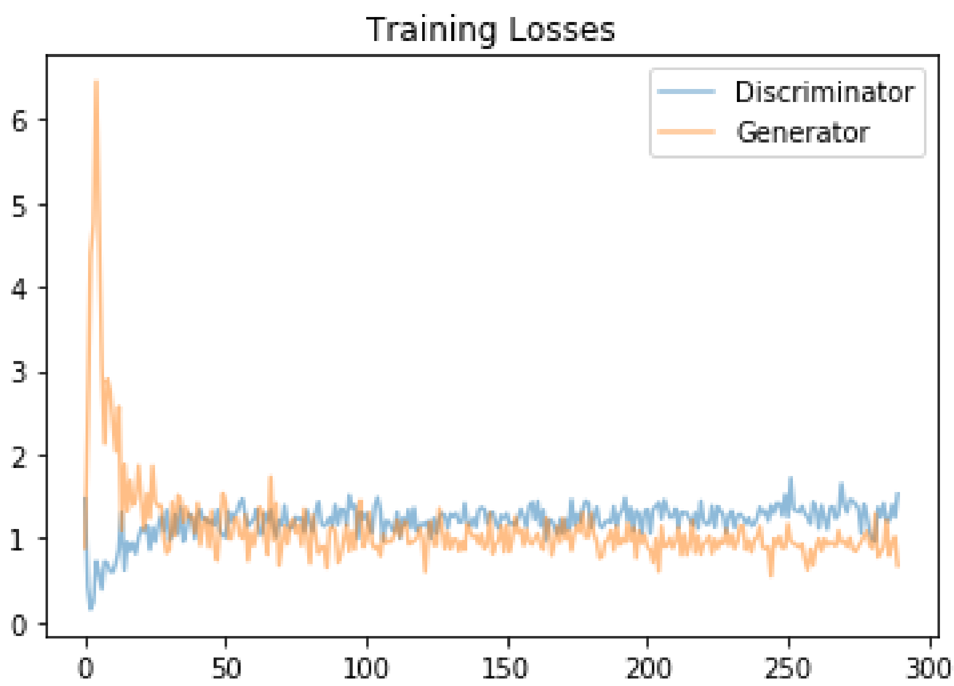
2.8 Training loss

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

In [26]:
```
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[26]: <matplotlib.legend.Legend at 0x7fa9cc181198>
```



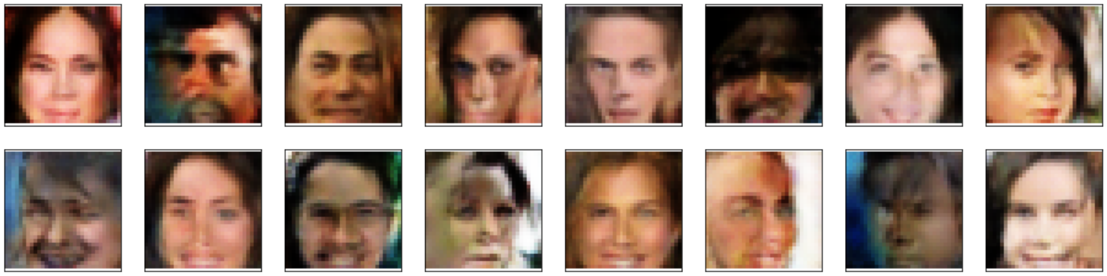
2.9 Generator samples from training

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

```
In [27]: # 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 [28]: # Load samples from generator, taken while training
         with open('train_samples.pkl', 'rb') as f:
             samples = pkl.load(f)
```

```
In [29]: _ = view_samples(-1, samples)
```



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

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

Answer: (Write your answer in this cell)
- Discriminator is very steady over time. We can observe squiggling up and down behavior as it's typical for adversarial network.
- Generator steadily decreases over time. For the most parts, generator loss value is slightly smaller than discriminator loss. Generator loss decreases a lot at the start of training (we can observe a huge spike). It is likely because it starts off producing really bad fakes. Then it made a big improvement, and after that it refined over time.
- Dropout layer in-between each of linear layers has been applied to ensure the network is likely to train each node evenly. - Having label smoothing will smooth our ground truth labels. It will make discriminator numerically stable and it will help discriminator to generalize better.
- Model produces low-resolution images.
- If weights are initialized in the network, it might help the model to converge faster.
- Higher number of epochs in most cases will produce better results at the price of training taking much longer time.
- Model can be improved even more by better tuning and optimization any of hyperparameters (like learning rate, batch size, etc.), as well as increasing depth by additional hidden layers.

2.9.2 Submitting This Project

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