dlnd_face_generation

June 28, 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()])
    image_dataset = datasets.ImageFolder(data_dir, transform)
    return torch.utils.data.DataLoader(image_dataset, batch_size = batch_size, shuffle=T
```

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 = 128
        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)
```

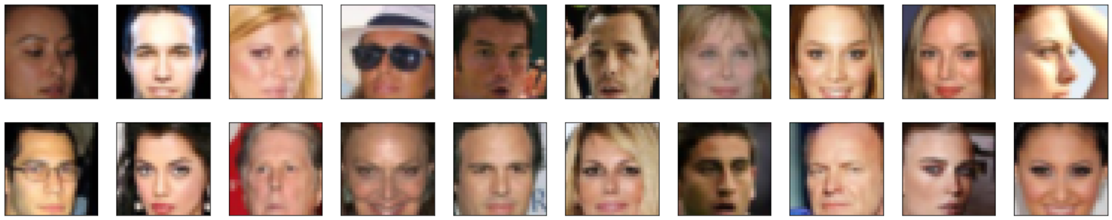
Next, you can view some images! You should seen square images of somewhat-centered faces.

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 [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
    return x * (max - min) + min
```

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(-0.9922)
Max:  tensor(0.2784)
```

---

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
```

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, out_channels,
                           kernel_size, stride, padding, bias=False)

    # append conv layer
    layers.append(conv_layer)

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

    # using Sequential container
    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 = conv(3, conv_dim, 4, batch_norm=False) # (16, 16, conv_dim)
        self.conv2 = conv(conv_dim, conv_dim*2, 4) # (8, 8, conv_dim*2)
        self.conv3 = conv(conv_dim*2, conv_dim*4, 4) # (4, 4, conv_dim*4)
        self.conv4 = conv(conv_dim*4, conv_dim*8, 4) # (2, 2, conv_dim*8)
```

```
        self.classifier = nn.Linear(conv_dim*8*2*2, 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
        out = F.leaky_relu(self.conv1(x), 0.2)
        out = F.leaky_relu(self.conv2(out), 0.2)
        out = F.leaky_relu(self.conv3(out), 0.2)
        out = F.leaky_relu(self.conv4(out), 0.2)

        out = out.view(-1, self.conv_dim*8*2*2)
        out = self.classifier(out)
        return out

"""
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]:
```
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

        self.fc = nn.Linear(z_size, conv_dim*8*2*2)

        self.t_conv1 = deconv(conv_dim*8, conv_dim*4, 4)
        self.t_conv2 = deconv(conv_dim*4, conv_dim*2, 4)
        self.t_conv3 = deconv(conv_dim*2, conv_dim, 4)
        self.t_conv4 = 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
        out = self.fc(x)
        out = out.view(-1, self.conv_dim*8, 2, 2) # (batch_size, depth, 4, 4)

        out = F.relu(self.t_conv1(out))
        out = F.relu(self.t_conv2(out))
        out = F.relu(self.t_conv3(out))

        # last layer: tanh activation instead of relu
        out = self.t_conv4(out)
        out = F.tanh(out)

        return out

"""
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]: 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:
                 nn.init.normal_(m.weight.data, 0.0, 0.02)
             elif classname.find('BatchNorm') != -1:
                 nn.init.normal_(m.weight.data, 1.0, 0.02)
                 nn.init.constant_(m.bias.data, 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 = 64
         g_conv_dim = 64
         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, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  )
  (conv2): 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)
  )
  (conv3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (conv4): Sequential(
    (0): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (classifier): Linear(in_features=2048, out_features=1, bias=True)
)

Generator(
  (fc): Linear(in_features=100, out_features=2048, bias=True)
  (t_conv1): Sequential(
```

```
    (0): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (t_conv2): Sequential(
    (0): ConvTranspose2d(256, 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)
  )
  (t_conv3): 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_conv4): Sequential(
    (0): ConvTranspose2d(64, 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 [18]: 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

         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.

In [19]:
```
import torch.optim as optim
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 [20]:
```
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()
```

```python
# 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
        # Compute the discriminator losses on real 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)

        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)
        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()

        # 2. Train the generator with an adversarial loss
        g_optimizer.zero_grad()

        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)
```

```
                D_fake = D(fake_images)
                g_loss = real_loss(D_fake)

                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 [21]: # set number of epochs
         n_epochs = 7


         """
         DON'T MODIFY ANYTHING IN THIS CELL
         """
         # call training function
         losses = train(D, G, n_epochs=n_epochs)
```

```
Epoch [    1/    7] | d_loss: 1.3437 | g_loss: 1.4623
Epoch [    1/    7] | d_loss: 0.1808 | g_loss: 4.6017
```

```
Epoch [    1/    7] | d_loss: 0.4086 | g_loss: 2.4095
Epoch [    1/    7] | d_loss: 0.3046 | g_loss: 2.9941
Epoch [    1/    7] | d_loss: 0.7858 | g_loss: 3.8346
Epoch [    1/    7] | d_loss: 0.8137 | g_loss: 5.4936
Epoch [    1/    7] | d_loss: 0.5189 | g_loss: 3.3199
Epoch [    1/    7] | d_loss: 0.5475 | g_loss: 3.6674
Epoch [    1/    7] | d_loss: 0.5942 | g_loss: 4.0014
Epoch [    1/    7] | d_loss: 0.4961 | g_loss: 3.3523
Epoch [    1/    7] | d_loss: 0.8930 | g_loss: 1.9572
Epoch [    1/    7] | d_loss: 0.6378 | g_loss: 2.5960
Epoch [    1/    7] | d_loss: 0.7803 | g_loss: 2.2604
Epoch [    1/    7] | d_loss: 0.5584 | g_loss: 3.4155
Epoch [    1/    7] | d_loss: 1.0980 | g_loss: 4.7654
Epoch [    2/    7] | d_loss: 0.9456 | g_loss: 1.6985
Epoch [    2/    7] | d_loss: 0.6704 | g_loss: 2.2194
Epoch [    2/    7] | d_loss: 0.7206 | g_loss: 2.7670
Epoch [    2/    7] | d_loss: 0.8976 | g_loss: 2.2704
Epoch [    2/    7] | d_loss: 0.8094 | g_loss: 1.9635
Epoch [    2/    7] | d_loss: 0.7082 | g_loss: 2.8806
Epoch [    2/    7] | d_loss: 0.7393 | g_loss: 2.3599
Epoch [    2/    7] | d_loss: 0.7140 | g_loss: 2.2049
Epoch [    2/    7] | d_loss: 0.8294 | g_loss: 1.8843
Epoch [    2/    7] | d_loss: 0.6283 | g_loss: 2.1773
Epoch [    2/    7] | d_loss: 1.1451 | g_loss: 3.5512
Epoch [    2/    7] | d_loss: 0.7456 | g_loss: 2.1122
Epoch [    2/    7] | d_loss: 0.5539 | g_loss: 2.1701
Epoch [    2/    7] | d_loss: 0.6095 | g_loss: 1.7768
Epoch [    2/    7] | d_loss: 0.5747 | g_loss: 2.1822
Epoch [    3/    7] | d_loss: 0.6626 | g_loss: 3.1909
Epoch [    3/    7] | d_loss: 0.8303 | g_loss: 2.0593
Epoch [    3/    7] | d_loss: 1.2030 | g_loss: 1.3203
Epoch [    3/    7] | d_loss: 0.8736 | g_loss: 3.0381
Epoch [    3/    7] | d_loss: 0.9104 | g_loss: 1.4243
Epoch [    3/    7] | d_loss: 0.7584 | g_loss: 1.8666
Epoch [    3/    7] | d_loss: 0.7212 | g_loss: 2.4640
Epoch [    3/    7] | d_loss: 0.9704 | g_loss: 1.0351
Epoch [    3/    7] | d_loss: 0.5350 | g_loss: 1.7317
Epoch [    3/    7] | d_loss: 0.9625 | g_loss: 1.0945
Epoch [    3/    7] | d_loss: 0.7676 | g_loss: 3.4429
Epoch [    3/    7] | d_loss: 0.5448 | g_loss: 1.9633
Epoch [    3/    7] | d_loss: 0.5370 | g_loss: 2.4156
Epoch [    3/    7] | d_loss: 0.6661 | g_loss: 2.9805
Epoch [    3/    7] | d_loss: 0.7960 | g_loss: 1.9922
Epoch [    4/    7] | d_loss: 0.6964 | g_loss: 2.8330
Epoch [    4/    7] | d_loss: 0.6284 | g_loss: 1.7921
Epoch [    4/    7] | d_loss: 0.9005 | g_loss: 1.5653
Epoch [    4/    7] | d_loss: 0.6507 | g_loss: 1.9150
Epoch [    4/    7] | d_loss: 0.6436 | g_loss: 2.9485
```

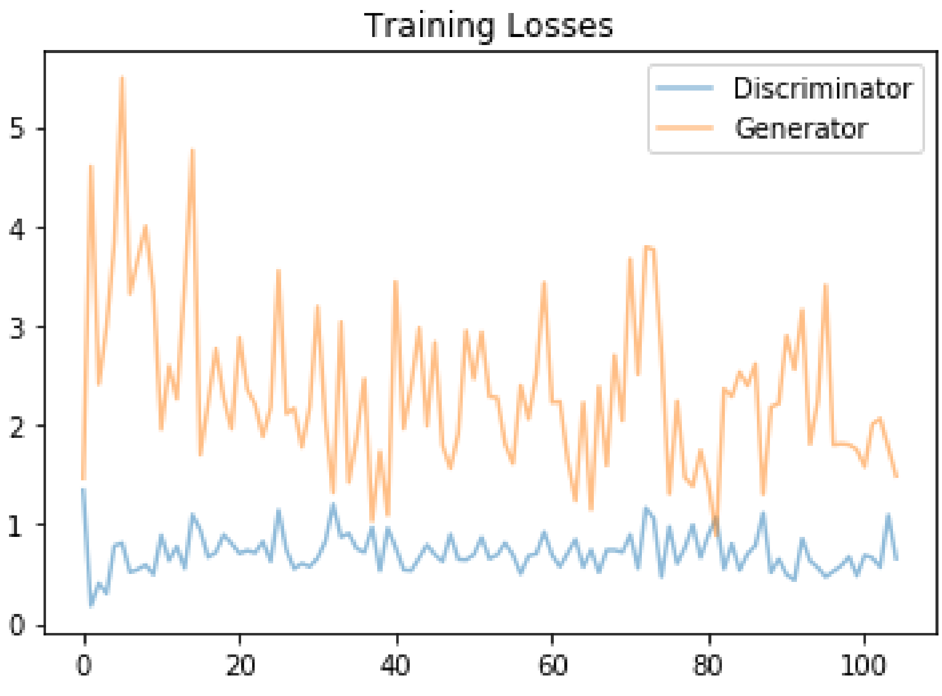
```
Epoch [    4/    7] | d_loss: 0.6977 | g_loss: 2.4649
Epoch [    4/    7] | d_loss: 0.8703 | g_loss: 2.9338
Epoch [    4/    7] | d_loss: 0.6558 | g_loss: 2.2860
Epoch [    4/    7] | d_loss: 0.6958 | g_loss: 2.2735
Epoch [    4/    7] | d_loss: 0.8142 | g_loss: 1.8117
Epoch [    4/    7] | d_loss: 0.6945 | g_loss: 1.6126
Epoch [    4/    7] | d_loss: 0.5048 | g_loss: 2.3966
Epoch [    4/    7] | d_loss: 0.6856 | g_loss: 2.0644
Epoch [    4/    7] | d_loss: 0.7057 | g_loss: 2.5178
Epoch [    4/    7] | d_loss: 0.9238 | g_loss: 3.4298
Epoch [    5/    7] | d_loss: 0.6955 | g_loss: 2.2265
Epoch [    5/    7] | d_loss: 0.5745 | g_loss: 2.2352
Epoch [    5/    7] | d_loss: 0.5185 | g_loss: 2.3851
Epoch [    5/    7] | d_loss: 0.7439 | g_loss: 1.5938
Epoch [    5/    7] | d_loss: 0.7433 | g_loss: 2.6999
Epoch [    5/    7] | d_loss: 0.7229 | g_loss: 2.0454
Epoch [    5/    7] | d_loss: 0.8959 | g_loss: 3.6700
Epoch [    5/    7] | d_loss: 0.5602 | g_loss: 2.5104
Epoch [    5/    7] | d_loss: 1.1643 | g_loss: 3.7888
Epoch [    5/    7] | d_loss: 1.0615 | g_loss: 3.7661
Epoch [    5/    7] | d_loss: 0.4750 | g_loss: 2.7299
Epoch [    6/    7] | d_loss: 0.9757 | g_loss: 1.3070
Epoch [    6/    7] | d_loss: 0.6079 | g_loss: 2.2403
Epoch [    6/    7] | d_loss: 0.7654 | g_loss: 1.4727
Epoch [    6/    7] | d_loss: 0.9962 | g_loss: 1.3832
Epoch [    6/    7] | d_loss: 0.6680 | g_loss: 1.7448
Epoch [    6/    7] | d_loss: 0.8952 | g_loss: 1.4150
Epoch [    6/    7] | d_loss: 1.0704 | g_loss: 0.8890
Epoch [    6/    7] | d_loss: 0.5539 | g_loss: 2.3630
Epoch [    6/    7] | d_loss: 0.8051 | g_loss: 2.2881
Epoch [    6/    7] | d_loss: 0.5421 | g_loss: 2.5312
Epoch [    6/    7] | d_loss: 0.7046 | g_loss: 2.3963
Epoch [    6/    7] | d_loss: 0.7867 | g_loss: 2.6125
Epoch [    7/    7] | d_loss: 0.8585 | g_loss: 3.1598
Epoch [    7/    7] | d_loss: 0.6355 | g_loss: 1.8086
Epoch [    7/    7] | d_loss: 0.5664 | g_loss: 2.2420
Epoch [    7/    7] | d_loss: 0.4735 | g_loss: 3.4055
Epoch [    7/    7] | d_loss: 0.5287 | g_loss: 1.8008
Epoch [    7/    7] | d_loss: 0.5850 | g_loss: 1.8114
Epoch [    7/    7] | d_loss: 0.6771 | g_loss: 1.8029
Epoch [    7/    7] | d_loss: 0.4845 | g_loss: 1.7537
Epoch [    7/    7] | d_loss: 0.6917 | g_loss: 1.5803
Epoch [    7/    7] | d_loss: 0.6641 | g_loss: 2.0089
Epoch [    7/    7] | d_loss: 0.5704 | g_loss: 2.0654
Epoch [    7/    7] | d_loss: 1.0926 | g_loss: 1.7776
Epoch [    7/    7] | d_loss: 0.6590 | g_loss: 1.4882
```

2.8 Training loss

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

```
In [22]: 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[22]: <matplotlib.legend.Legend at 0x7f60976a10b8>
```



2.9 Generator samples from training

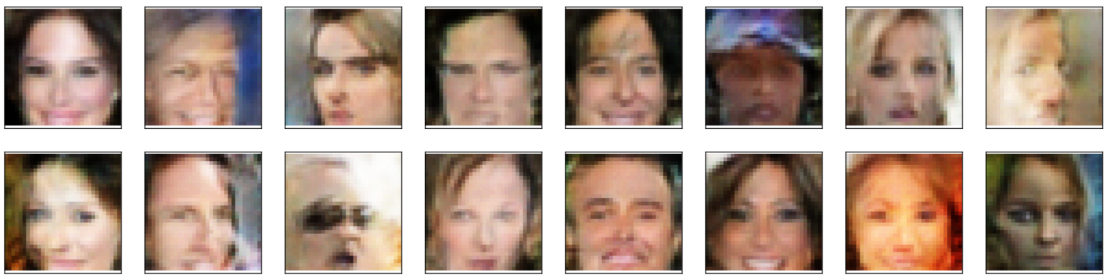
View samples of images from the generator, and answer a question about the strengths and weaknesses of your trained models.

```
In [23]: # 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 [24]:
```
# Load samples from generator, taken while training
with open('train_samples.pkl', 'rb') as f:
    samples = pkl.load(f)
```

In [25]:
```
_ = 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: With increase number of epochs.It will take some more time but model is improved upto a particular point.Image are of very low resolution.Most of the celibrity was white.

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.