Fake Face Generator Using DCGAN Model

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Overview

In the following article, we will define and train a **Deep Convolutional Generative Adversarial Network*(DCGAN)*** model on a dataset of faces. The main objective of the model is to get a Generator Network to generate new images of fake human faces that look as realistic as possible.

To do so, we will first try to understand the intuition behind the working of ***GAN***s and ***DCGAN***s and then combine this knowledge to build a **Fake Face Generator Model**. By the end of this post, you will be able to generate your fake samples on any given dataset, using the concepts from this article.

Introduction

The following article is divided into two sections:

- **Theory** — Understanding the intuition behind the working of *GAN*s and *DCGAN*s.
- **Practical** — Implementing Fake Face Generator in Pytorch.

This article would be covering both sections. So let's begin the journey….

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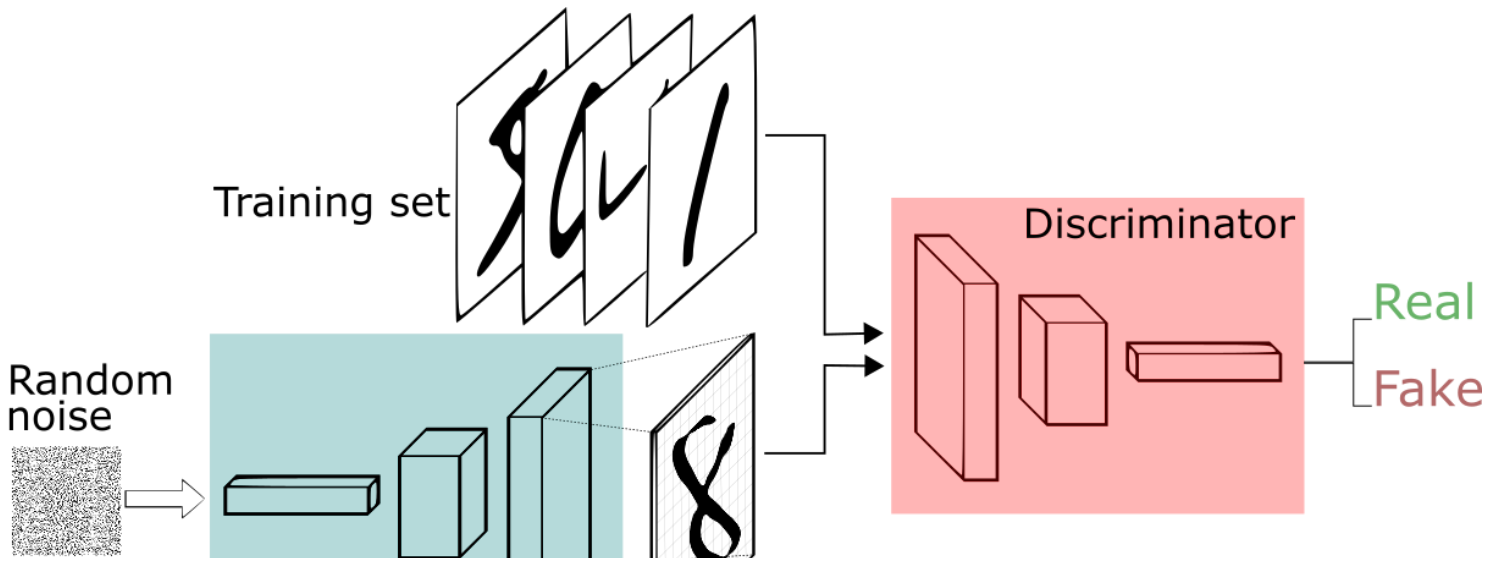
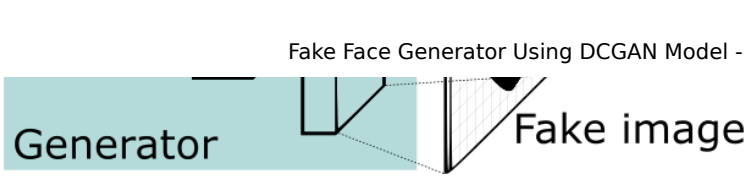
Theory

Intuition Behind Generative Adversarial Networks(GANs)





Generative Adversarial Network(GAN) architecture. Image from https://sthalles.github.io/intro-to-gans/

- **Definition**

*GAN*s, in general, can be defined as a generative model that lets us generate a whole image in parallel. Along with several other kinds of generative models, *GAN*s uses a differentiable function represented by a neural network as a *Generator Network*.

- **Generator Network**

The Generator Network takes random noise as input, then runs the noise through the differentiable function*(neural network)* to transform the noise and reshape it to have a recognizable structure similar to the images in the training dataset. The output of the Generator is determined by the choice of the input random noise. Running the Generator Network over several different random input noises results in different realistic output images.

The end goal of the Generator is to learn a distribution similar to the distribution of the training dataset to sample out realistic images. To be able to do so, the Generator Network needs to be trained. The training process of the *GAN*s is very different, compared to other generative models*(Most generative models are trained by adjusting the parameters to maximize the probability of Generator to generate realistic samples.For-eg Variational Auto-Encoders(VAE))*. *GAN*s, on the other hand, uses a second network to train the Generator, called *Discriminator Network*.

- **Discriminator Network**

Discriminator Network is a basic classifier network that outputs the probability of an image to be real. So, during the training process, the Discriminator Network is shown real images from the training set half the time and fake images from Generator another half of the time. The Discriminator target is to assign a probability near 1, for real images and probability near 0, for fake images.

On the other hand, Generator tries the opposite, its target is to generate fake images, for which Discriminator would result in a probability close to 1*(considering them to be real images from the training set)*. As training goes on, the Discriminator will become better at classifying real and fake images. So to fool the Discriminator, Generator will be forced to improve to produce more realistic samples. So we can say that:

> GANs can be considered as a two-player(Generator and Discriminator)non-cooperative game, where each player wishes to minimize its cost function.

Difference Between GANs and DCGANs

*DCGAN*s are very similar to *GAN*s but specifically focuses on using deep convolutional networks in place of fully-connected networks used in Vanilla *GAN*s.

Convolutional networks help in finding deep correlation within an image, that is they look for spatial correlation. This means DCGAN would be a better option for image/video data, whereas *GAN*s can be considered as a general idea on which *DCGAN*s and many other architectures *(CGAN, CycleGAN, StarGAN and many others)* have been developed.

> *In this article, we are mainly working on image data, this means that DCGAN would be a better option compared to Vanilla GAN. So from now on, we will be mainly focussing on DCGANs.*

Some Tips For Training DCGANs

> *All the training tips can also be applied to Vanilla GANs as well.*

- Make sure that both Discriminator and Generator have at least one hidden layer. This makes sure both the models have a ***Universal Approximation Property***.

> ***Universal Approximation Property*** *states that a feed-forward network with a single hidden layer containing a finite number of hidden units can approximate any probability distribution, given enough hidden units.*

- For the hidden units, many activation functions could work, but Leaky ReLUs are the most popular. Leaky ReLUs make sure that gradient flows through the entire architecture. This is very important for *DCGAN*s because the only way the Generator can learn is to receive a gradient from the Discriminator.

- One of the most popular activation function for the output of the Generator Network is the Tangent Hyperbolic Activation Function*(Based on the Improved Training Techniques For GANs paper)*.

- As the Discriminator is a binary classifier, we will be using the Sigmoid Activation Function to get the final probability.

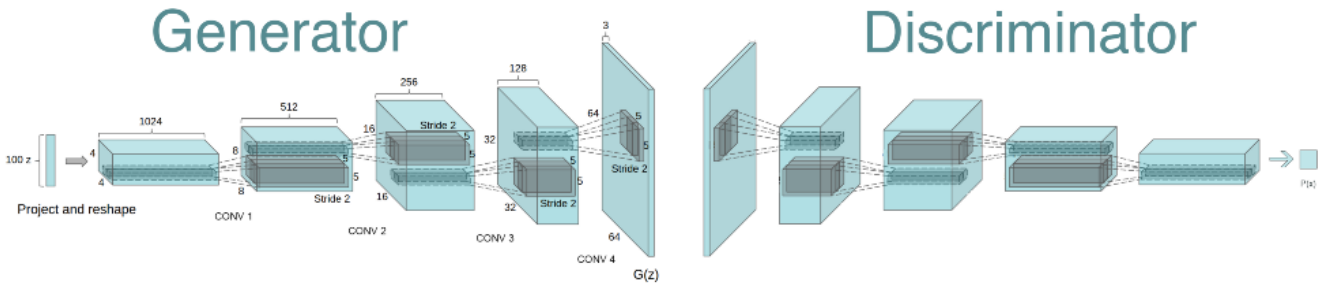
So far, we have talked about the working intuition and some tips and tricks for training *GAN*s/*DCGAN*s. But still, many questions are left unanswered. Some of them are:

> *Which optimizer to choose? How is the cost function defined? How long does a network need to be trained? and many others, that would be covered in the* ***Practical*** *section.*

. . .

Practical

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



DCGAN Architecture. Image from https://gluon.mxnet.io/chapter14_generative-adversarial-networks/dcgan.html

(1)Get The Data

You'll be using the CelebFaces Attributes Dataset *(CelebA)* to train your adversarial networks. This data is a more complex dataset compared to the MNIST. So, we need to define a deeper network*(DCGAN)* to generate good results. I would suggest you use a GPU for training purposes.

(2)Preparing Data

As the main objective of this article is building a *DCGAN* model, so instead of doing the preprocessing ourselves, we will be using a pre-processed dataset. You can download the smaller subset of the **CelebA** dataset from here. And if you are interested in doing the pre-processing, do the following:

- Crop images to remove the part that doesn't include the face.
- Resize them into 64x64x3 *NumPy* images.

Now, we will create a *DataLoader* to access the images in batches.

```
def get_dataloader(batch_size, image_size, data_dir='train/'):
    """
    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
    """
    transform =
transforms.Compose([transforms.Resize(image_size),transforms.CenterCr
op(image_size),transforms.ToTensor()])

    dataset = datasets.ImageFolder(data_dir,transform = transform)

    dataloader = torch.utils.data.DataLoader(dataset =
dataset,batch_size = batch_size,shuffle = True)
    return dataloader

# Define function hyperparameters
batch_size = 256
img_size = 32

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

DataLoader hyperparameters:

- You can decide on any reasonable *batch_size* parameter.
- However, 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.

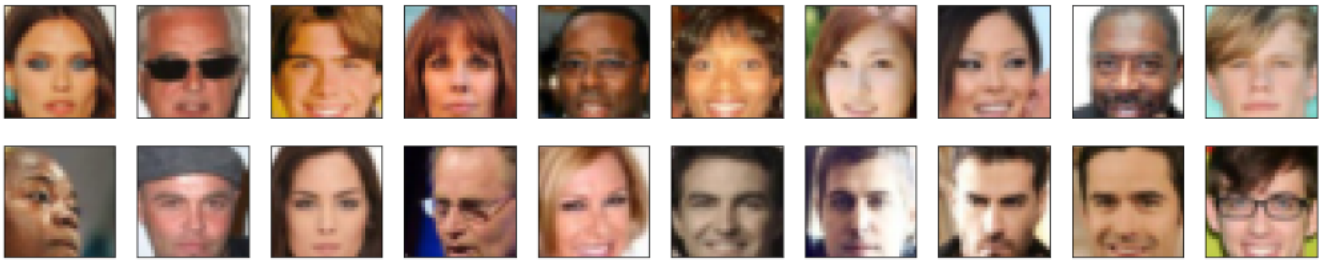
Next, we will write some code to get a visual representation of the dataset.

```
def imshow(img):
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))

# 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])
```

Keep in mind to convert the *Tensor* images into a *NumPy* type and transpose the dimensions to correctly display an image based on the above code*(In Dataloader we transformed the images to Tensor)*. Run this piece of code to get a visualization of the dataset.



Images Centered around faces

Now before beginning with the next section*(Defining Model),* we will write a function to scale the image data to a pixel range of -1 to 1 which we will use while training. The

reason behind doing so is 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 the range 0–1)*.

```
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
```

(3)Defining Model

A *GAN* is comprised of two adversarial networks, a discriminator and a generator. So in this section, we will define architectures for both of them.

Discriminator

This is a convolutional classifier, only without any *MaxpPooling* layers. Here is the code for the Discriminator Network.

```
def conv(input_c,output,kernel_size,stride = 2,padding  = 1,
batch_norm = True):
    layers =[]
    con = nn.Conv2d(input_c,output,kernel_size,stride,padding,bias =
False)
    layers.append(con)

    if batch_norm:
        layers.append(nn.BatchNorm2d(output))

    return nn.Sequential(*layers)

class Discriminator(nn.Module):

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

```
        """
        #complete init function

    super(Discriminator, self).__init__()
        self.conv_dim = conv_dim
        self.layer_1 = conv(3,conv_dim,4,batch_norm = False) #16
        self.layer_2 = conv(conv_dim,conv_dim*2,4) #8
        self.layer_3 = conv(conv_dim*2,conv_dim*4,4) #4
        self.fc = nn.Linear(conv_dim*4*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.layer_1(x))
        x = F.leaky_relu(self.layer_2(x))
        x = F.leaky_relu(self.layer_3(x))
        x = x.view(-1,self.conv_dim*4*4*4)
        x = self.fc(x)
        return x
```

Explanation

- The following architecture consists of three convolutional layers and a final fully connected layer, which output a single logit. This logit defines whether the image is real or not.
- Each convolution layer, except the first one, is followed by a *Batch Normalization(defined in conv helper function)*.
- For the hidden units, we have used the *leaky ReLU* activation function as discussed in the **theory** section.
- After each convolution layer, the height and width become half. For-eg After the first convolution 32X32 images will be resized into 16X16 and so on.

> *Output dimension can be calculated using the following formula:*

$$O = \frac{W-K+2P}{S} + 1$$

Formula-1

> *where* O *is the output height/length,* W *is the input height/length,* K *is the filter size,* P *is the padding, and* S *is the stride.*

- The number of feature maps after each convolution is based on the parameter *conv_dim(In my implementation conv_dim = 64)*.

In this model definition, we haven't applied the *Sigmoid* activation function on the final output logit. This is because of the choice of our loss function. Here instead of using the normal *BCE(Binary Cross-Entropy Loss),* we will be using *BCEWithLogitLoss,* which is considered as a numerically stable version of *BCE*. *BCEWithLogitLoss* is defined such that it first applies Sigmoid activation function on the logit and then calculates the loss, unlike *BCE*. You can read more about these loss functions here.

Generator

The generator should upsample an input and generate a new image of the same size as our training data 32X32X3. For doing so we will be using transpose convolutional layers. Here is the code for the Generator Network.

```
def deconv(input_c,output,kernel_size,stride = 2, padding =1,
batch_norm = True):
    layers = []
    decon =
nn.ConvTranspose2d(input_c,output,kernel_size,stride,padding,bias =
False)
    layers.append(decon)

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

class Generator(nn.Module):

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

```
        self.conv_dim = conv_dim
        self.fc = nn.Linear(z_size,conv_dim*8*2*2)
        self.layer_1 = deconv(conv_dim*8,conv_dim*4,4) #4
        self.layer_2 = deconv(conv_dim*4,conv_dim*2,4) #8
        self.layer_3 = deconv(conv_dim*2,conv_dim,4) #16
        self.layer_4 = deconv(conv_dim,3,4,batch_norm = False) #32


    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)
        x = x.view(-1,self.conv_dim*8,2,2) #
(batch_size,depth,width,height)
        x = F.relu(self.layer_1(x))
        x = F.relu(self.layer_2(x))
        x = F.relu(self.layer_3(x))
        x = torch.tanh(self.layer_4(x))
        return x
```

Explanation

- The following architecture consists of a fully connected layer followed by four transpose convolution layers. This architecture is defined such that the output after the fourth transpose convolution layer results in an image of dimension 32X32X3*(size of an image from training dataset)*.
- The inputs to the generator are vectors of some length *z_size(z_size is the noise vector)*.
- Each transpose convolution layer, except the last one, is followed by a *Batch Normalization(defined in deconv helper function)*.
- For the hidden units, we have used the *ReLU* activation function.
- After each transpose convolution layer, the height and width become double. For-eg After the first transpose convolution 2X2 images will be resized into 4X4 and so on.

> *Can be calculated using the following formula:*

```
 # Padding==Same:
H = H1 * stride

 # Padding==Valid
H = (H1-1) * stride + HF
```

where H = output size, H1 = input size, HF = filter size.

- The number of feature maps after each transpose convolution is based on the parameter *conv_dim(In my implementation conv_dim = 64)*.

(4)Initialize The Weights Of Your Networks

To help the models converge, I initialized the weights of the convolutional and linear layers in the model based on the original *DCGAN* paper, which says: All weights are initialized from a zero-centered Normal distribution with a standard deviation of 0.02.

```
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__

    if hasattr(m,'weight') and (classname.find('Conv') != -1 or
classname.find('Linear') != -1):

        m.weight.data.normal_(0.0,0.02)

        if hasattr(m,'bias') and m.bias is not None:
            m.bias.data.zero_()
```

- This would initialize the weights to a normal distribution, centered around 0, with a standard deviation of 0.02.
- The bias terms, if they exist, maybe left alone or set to 0.

(5)Build Complete Network

Define your models' hyperparameters and instantiate the discriminator and generator from the classes defined in the **Defining Model** section. Here is the code for that.

```
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

# Define model hyperparams
d_conv_dim = 64
g_conv_dim = 64
z_size = 100

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

When you run the above code you get the following output. It also describes the model architecture for the Discriminator and Generator models.

```
Discriminator(
  (layer_1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  )
  (layer_2): 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)
  )
  (layer_3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1,
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
  )
  (fc): Linear(in_features=4096, out_features=1, bias=True)
)

Generator(
  (fc): Linear(in_features=100, out_features=2048, bias=True)
  (layer_1): 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)
  )
```

```
    (layer_2): 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)
    )
    (layer_3): 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)
    )
    (layer_4): Sequential(
      (0): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    )
  )
```

Instantiated **Discriminator** and **Generator** models

(6)Training Process

> *The training process comprises defining the loss functions, selecting optimizer and finally training the model.*

Discriminator And Generator Loss

Discriminator Loss

- For the discriminator, the total loss is the sum of *(d_real_loss + d_fake_loss)*, where *d_real_loss* is the loss obtained on images from the training data and *d_fake_loss* is the loss obtained on images generated from Generator Network. For-eg

> *z — Noise vector*
>
> *i — Image from the training set*
>
> *G(z) — Generated image*
>
> *D(G(z)) — Discriminator output on a generated image*
>
> *D(i) — Discriminator output on a training dataset image*
>
> *Loss = real_loss(D(i)) + fake_loss(D(G(z)))*

- 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*(Keep this line in mind while reading the code below)*.

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*. For-eg

> *z — Noise vector*
>
> *G(z) — Generated Image*
>
> *D(G(z)) — Discriminator output on a generated image*
>
> *Loss = real_loss(D(G(z)))*

Here is the code for *real_loss* and *fake_loss*

```
def real_loss(D_out):
    '''Calculates how close discriminator outputs are to being real.
       param, D_out: discriminator logits
       return: real loss'''
    batch_size = D_out.size(0)
    labels = torch.ones(batch_size)
    if train_on_gpu:
        labels = labels.cuda()
    criterion = nn.BCEWithLogitsLoss()
    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)
    if train_on_gpu:
        labels = labels.cuda()
    criterion =  nn.BCEWithLogitsLoss()
    loss = criterion(D_out.squeeze(),labels)
    return loss
```

Optimizers

For *GAN*s we define two optimizers, one for the Generator and another for the Discriminator. The idea is to run them simultaneously to keep improving both the

networks. In this implementation, I have used *Adam* optimizer in both cases. To know more about different optimizers, refer to this link.

```
# Create optimizers for the discriminator D and generator G
d_optimizer = optim.Adam(D.parameters(),lr = .0002, betas =
[0.5,0.999])
g_optimizer = optim.Adam(G.parameters(),lr = .0002, betas =
[0.5,0.999])
```

Learning rate(lr) and *betas* values are based on the original DCGAN paper.

Training

Training will involve alternating between training the discriminator and the generator. We'll use the *real_loss* and *fake_loss* functions defined earlier, to help us in calculating the Discriminator and Generator 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

Here is the code for training.

```
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)
            if train_on_gpu:
                real_images = real_images.cuda()

            # 1. Train the discriminator on real and fake ima.ges
            d_optimizer.zero_grad()
            d_out_real = D(real_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()
            d_loss = real_loss(d_out_real) + fake_loss(D(G(z)))
            d_loss.backward()
            d_optimizer.step()
            # 2. Train the generator with an adversarial loss
            G.train()
            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()
            g_loss = real_loss(D(G(z)))
            g_loss.backward()
            g_optimizer.step()

            # 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 number of epochs
n_epochs = 40

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

> *The training is performed over 40 epochs using a GPU, that's why I had to move my models and inputs from CPU to GPU.*

(6)Results

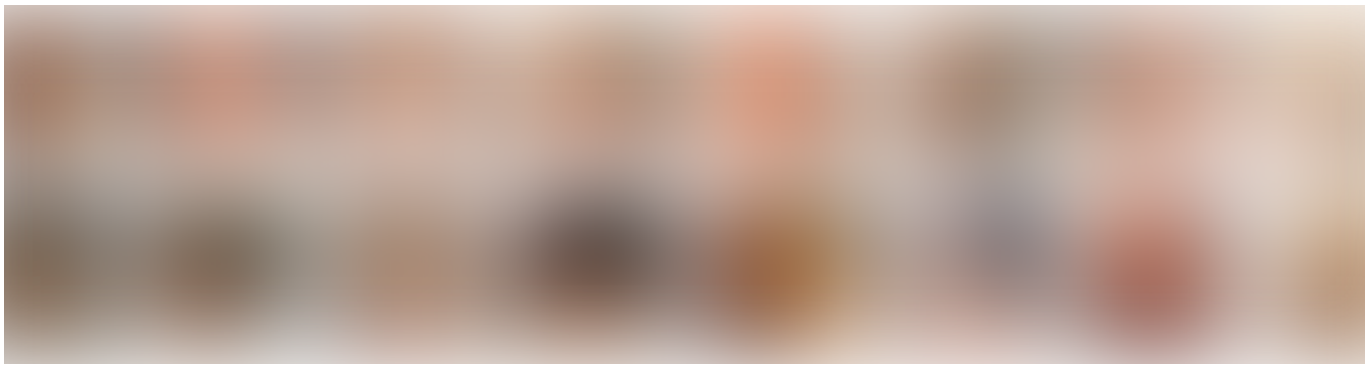
- The following is the plot of the training losses for the Generator and Discriminator recorded after each epoch.

Training Loss for **Discriminator** and **Generator**

The high fluctuation in the Generator training loss is because the input to the Generator Network is a batch of random noise vectors *(each of z_size)*, each sampled from a uniform distribution of (-1,1) to generate new images for each epoch.

In the discriminator plot, we can observe a rise in the training loss *(around 50 on the x-axis)* followed by a gradual decrease till the end, this is because the Generator has started to generate some realistic image that fooled the Discriminator, leading to increase in error. But slowly as the training progresses, Discriminator becomes better at classifying fake and real images, leading to a gradual decrease in training error.

- Generated samples after *40 epochs*.



Generated fake images

Our model was able to generate new images of fake human faces that look as realistic as possible. We can also observe that all images are lighter in shade, even the brown faces are bit lighter. This is because the **CelebA** dataset is biased; it consists of "celebrity" faces that are mostly white. That being said, DCGAN successfully generates near-real images from mere noise.

. . .

Image from https://memeshappen.com/meme/success-kid-original/finally-we-did-it-6891/5

Reference

- DCGAN original paper
- Udacity Deep Learning Nanodegree course

Check out my Github repo regarding this post.

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