# 1 GAN

```
import os, sys

# Add DLStudio-2.5.2 and AdversarialLearning to sys.path so Python can
find DLStudio and AdversarialLearning
current_dir = os.getcwd()
print("current_dir = %s" % current_dir)

DLStudio_dir = os.path.join(current_dir, "../DLStudio-2.5.2")

sys.path.append(DLStudio_dir)

from DLStudio import *
```

```
current_dir = d:\MS Purdue\1.5\ECE60146\HW9
```

## 1.1 Model

I tried training my own model, but it collapsed lol. Additionally, I also tried default setting for CG2 in DLStudio; however, mode collapse occured. Every generated image is an identical, abstract pattern that does not resemble human faces. Interestingly, the default setting for DG2 in DLStudio don't lead to mode collapse. However, when I **lowered** the learning rate for DG2, mode collapse started to occur — further investigation is needed.

```
# the code below is mainly borrowed from DLSudio-2.5.2

from DLStudio import DLStudio

import sys,os,os.path
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
import torchvision.transforms as tvt
import torchvision.transforms.functional as tvtF
import torch.optim as optim
import numpy as np
import math
import random
import matplotlib.pyplot as plt
import matplotlib.animation as animation
import time
import glob

import imageio
```

```
class MyAdversarialLearning(object):

    def __init__(self, *args, **kwargs ):
        if args:
            raise ValueError(
                   '''AdversarialLearning constructor can only be
called with keyword arguments for the following
                      keywords: epochs, learning_rate, batch_size,
momentum, image_size, dataroot, path_saved_model,
                      use_gpu, latent_vector_size, ngpu, dlstudio,
device, LAMBDA, clipping_threshold, and beta1''')
        allowed_keys =
'dataroot','image_size','path_saved_model','momentum','learning_rate',
'epochs','batch_size', \

'classes','use_gpu','latent_vector_size','ngpu','dlstudio', 'beta1',
'LAMBDA', 'clipping_threshold'
        keywords_used = kwargs.keys()

        for keyword in keywords_used:

            if keyword not in allowed_keys:

                raise SyntaxError(keyword + ":  Wrong keyword used ---
check spelling")
        learning_rate = epochs = batch_size = convo_layers_config =
momentum = None
        image_size = fc_layers_config = dataroot =  path_saved_model =
classes = use_gpu = None
        latent_vector_size = ngpu = beta1 = LAMBDA =
clipping_threshold = None
        if 'latent_vector_size' in kwargs            :
latent_vector_size = kwargs.pop('latent_vector_size')
        if 'ngpu' in kwargs                          :   ngpu  =
kwargs.pop('ngpu')
        if 'dlstudio' in kwargs                      :   dlstudio  =
kwargs.pop('dlstudio')
        if 'beta1' in kwargs                         :   beta1  =
kwargs.pop('beta1')
        if 'LAMBDA' in kwargs                        :   LAMBDA  =
kwargs.pop('LAMBDA')
        if 'clipping_threshold' in kwargs            :
clipping_threshold = kwargs.pop('clipping_threshold')
        if latent_vector_size:
            self.latent_vector_size = latent_vector_size
        if ngpu:
            self.ngpu = ngpu
        if dlstudio:
            self.dlstudio = dlstudio
        if beta1:
```

```
            self.beta1 = beta1
        if LAMBDA:
            self.LAMBDA = LAMBDA
        if clipping_threshold:
            self.clipping_threshold = clipping_threshold



    def show_sample_images_from_dataset(self, dlstudio):
        data = next(iter(self.train_dataloader))
        real_batch = data[0]

self.dlstudio.display_tensor_as_image(torchvision.utils.make_grid(real
_batch, padding=2, pad_value=1, normalize=True))


    def set_dataloader(self):
        dataset =
torchvision.datasets.ImageFolder(root=self.dlstudio.dataroot,
                       transform = tvt.Compose([

tvt.Resize(self.dlstudio.image_size),

tvt.CenterCrop(self.dlstudio.image_size),
                                            tvt.ToTensor(),

                                            tvt.Normalize((0.5, 0.5,
0.5), (0.5, 0.5, 0.5)),
                       ]))
        self.train_dataloader = torch.utils.data.DataLoader(dataset,
batch_size=self.dlstudio.batch_size,

shuffle=True, num_workers=2)

    def weights_init(self,m):
        """
        Uses the DCGAN initializations for the weights
        """
        classname = m.__class__.__name__
        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)


    def calc_gradient_penalty(self, netC, real_data, fake_data):
        """
        Implementation by Marvin Cao: https://github.com/caogang/wgan-
gp
```

```
        Marvin Cao's code is a PyTorch version of the Tensorflow based
implementation provided by
        the authors of the paper "Improved Training of Wasserstein
GANs" by Gulrajani, Ahmed,
        Arjovsky, Dumouli,  and Courville.
        """
        BATCH_SIZE = self.dlstudio.batch_size
        LAMBDA = self.LAMBDA
        epsilon = torch.rand(1).cuda()
        interpolates = epsilon * real_data + ((1 - epsilon) *
fake_data)
        interpolates = interpolates.requires_grad_(True).cuda()
        critic_interpolates = netC(interpolates)
        gradients = torch.autograd.grad(outputs=critic_interpolates,
inputs=interpolates,

grad_outputs=torch.ones(critic_interpolates.size()).cuda(),
                                  create_graph=True,
retain_graph=True, only_inputs=True)[0]
        gradient_penalty = ((gradients.norm(2, dim=1) - 1) **
2).mean() * LAMBDA
        return gradient_penalty


    def close_event(self):
        '''
        from stackoverflow.com
        '''
        plt.close()

    class DiscriminatorDG2(nn.Module):
        """
        This is essentially the same network as the DCGAN for DG1,
except for the extra layer
        "self.extra" shown below.  We also declare a batchnorm for
this extra layer in the form
        of "self.bnX".  In the implementation of "forward()", we
invoke the extra layer at the
        beginning of the network.

        Class Path:  AdversarialLearning  ->   DiscriminatorDG2
        """
        def __init__(self, skip_connections=True, depth=16):
            super(MyAdversarialLearning.DiscriminatorDG2,
self).__init__()
            self.conv_in = nn.Conv2d(  3,    64,      kernel_size=4,
stride=2,    padding=1)
            self.extra =   nn.Conv2d(  64,    64,      kernel_size=4,
stride=1,    padding=2)
            self.conv_in2 = nn.Conv2d( 64,   128,     kernel_size=4,
```

```
stride=2,    padding=1)
            self.conv_in3 = nn.Conv2d( 128,  256,     kernel_size=4,
stride=2,    padding=1)
            self.conv_in4 = nn.Conv2d( 256,  512,     kernel_size=4,
stride=2,    padding=1)
            self.conv_in5 = nn.Conv2d( 512,  1,       kernel_size=4,
stride=1,    padding=0)
            self.bn1  = nn.BatchNorm2d(128)
            self.bn2  = nn.BatchNorm2d(256)
            self.bn3  = nn.BatchNorm2d(512)
            self.bnX  = nn.BatchNorm2d(64)
            self.sig = nn.Sigmoid()
        def forward(self, x):
            x = torch.nn.functional.leaky_relu(self.conv_in(x),
negative_slope=0.2, inplace=True)
            x = self.bnX(self.extra(x))
            x = torch.nn.functional.leaky_relu(x, negative_slope=0.2,
inplace=True)
            x = self.bn1(self.conv_in2(x))
            x = torch.nn.functional.leaky_relu(x, negative_slope=0.2,
inplace=True)
            x = self.bn2(self.conv_in3(x))
            x = torch.nn.functional.leaky_relu(x, negative_slope=0.2,
inplace=True)
            x = self.bn3(self.conv_in4(x))
            x = torch.nn.functional.leaky_relu(x, negative_slope=0.2,
inplace=True)
            x = self.conv_in5(x)
            x = self.sig(x)
            return x

    class GeneratorDG2(nn.Module):
        """
        The Generator for DG2 is exactly the same as for the DG1.  So
please the comment block for that
        Generator.

        Class Path:  AdversarialLearning  ->   GeneratorDG2
        """
        def __init__(self):
            super(MyAdversarialLearning.GeneratorDG2, self).__init__()
            self.latent_to_image = nn.ConvTranspose2d( 100,   512,
kernel_size=4, stride=1, padding=0, bias=False)
            self.upsampler2 = nn.ConvTranspose2d( 512, 256,
kernel_size=4, stride=2, padding=1, bias=False)
            self.upsampler3 = nn.ConvTranspose2d (256, 128,
kernel_size=4, stride=2, padding=1, bias=False)
            self.upsampler4 = nn.ConvTranspose2d (128, 64,
kernel_size=4, stride=2, padding=1, bias=False)
```

```
            self.upsampler5 = nn.ConvTranspose2d(  64,  3,
kernel_size=4, stride=2, padding=1, bias=False)
            self.bn1 = nn.BatchNorm2d(512)
            self.bn2 = nn.BatchNorm2d(256)
            self.bn3 = nn.BatchNorm2d(128)
            self.bn4 = nn.BatchNorm2d(64)
            self.tanh  = nn.Tanh()
        def forward(self, x):
            x = self.latent_to_image(x)
            x = torch.nn.functional.relu(self.bn1(x))
            x = self.upsampler2(x)
            x = torch.nn.functional.relu(self.bn2(x))
            x = self.upsampler3(x)
            x = torch.nn.functional.relu(self.bn3(x))
            x = self.upsampler4(x)
            x = torch.nn.functional.relu(self.bn4(x))
            x = self.upsampler5(x)
            x = self.tanh(x)
            return x
    ########################################   DG2 Definition ENDS
###########################################




######################################################################
######################################
    ##  The training routines follow, first for a GAN constructed
using either the DG1 and or the DG2
    ##  Discriminator-Generator Networks, and then for a WGAN
constructed using either the CG1 or the CG2
    ##  Critic-Generator Networks.

######################################################################
######################################

    def run_gan_code(self, dlstudio, discriminator, generator,
results_dir):
        """
        This function is meant for training a Discriminator-Generator
based Adversarial Network.
        The implementation shown uses several programming constructs
from the "official" DCGAN
        implementations at the PyTorch website and at GitHub.

        Regarding how to set the parameters of this method, see the
following script

                     dcgan_DG1.py
```

```
        in the "ExamplesAdversarialLearning" directory of the
distribution.
        """
        dir_name_for_results = results_dir
        if os.path.exists(dir_name_for_results):
            files = glob.glob(dir_name_for_results + "/*")
            for file in files:
                if os.path.isfile(file):
                    os.remove(file)
                else:
                    files = glob.glob(file + "/*")
                    list(map(lambda x: os.remove(x), files))
        else:
            os.mkdir(dir_name_for_results)
        #  Set the number of channels for the 1x1 input noise vectors
for the Generator:
        nz = 100
        netD = discriminator.to(self.dlstudio.device)
        netG = generator.to(self.dlstudio.device)
        #  Initialize the parameters of the Discriminator and the
Generator networks according to the
        #  definition of the "weights_init()" method:
        netD.apply(self.weights_init)
        netG.apply(self.weights_init)
        #  We will use a the same noise batch to periodically check on
the progress made for the Generator:
        fixed_noise = torch.randn(self.dlstudio.batch_size, nz, 1, 1,
device=self.dlstudio.device)
        #  Establish convention for real and fake labels during
training
        real_label = 1
        fake_label = 0
        #  Adam optimizers for the Discriminator and the Generator:
        optimizerD = optim.Adam(netD.parameters(),
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        optimizerG = optim.Adam(netG.parameters(),
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        #  Establish the criterion for measuring the loss at the
output of the Discriminator network:
        criterion = nn.BCELoss()
        #  We will use these lists to store the results accumulated
during training:
        img_list = []
        G_losses = []
        D_losses = []
        iters = 0
        print("\n\nStarting Training Loop...\n\n")
        start_time = time.perf_counter()
        for epoch in range(dlstudio.epochs):
```

```
            g_losses_per_print_cycle = []
            d_losses_per_print_cycle = []
            # For each batch in the dataloader
            for i, data in enumerate(self.train_dataloader, 0):


                ##  Maximization Part of the Min-Max Objective of Eq.
(3):
                ##
                ##  As indicated by Eq. (3) in the DCGAN part of the
doc section at the beginning of this
                ##  file, the GAN training boils down to carrying out
a min-max optimization. Each iterative
                ##  step of the max part results in updating the
Discriminator parameters and each iterative
                ##  step of the min part results in the updating of
the Generator parameters.  For each
                ##  batch of the training data, we first do max and
then do min.  Since the max operation
                ##  affects both terms of the criterion shown in the
doc section, it has two parts: In the
                ##  first part we apply the Discriminator to the
training images using 1.0 as the target;
                ##  and, in the second part, we supply to the
Discriminator the output of the Generator
                ##  and use 0 as the target. In what follows, the
Discriminator is being applied to
                ##  the training images:
                netD.zero_grad()
                real_images_in_batch =
data[0].to(self.dlstudio.device)
                #  Need to know how many images we pulled in since at
the tailend of the dataset, the
                #  number of images may not equal the user-specified
batch size:
                b_size = real_images_in_batch.size(0)
                label = torch.full((b_size,), real_label,
dtype=torch.float, device=self.dlstudio.device)
                output = netD(real_images_in_batch).view(-1)
                lossD_for_reals = criterion(output, label)

                lossD_for_reals.backward()

                ##  That brings us the second part of what it takes to
carry out the max operation on the
                ##  min-max criterion shown in Eq. (3) in the doc
section at the beginning of this file.
                ##  part calls for applying the Discriminator to the
images produced by the Generator from
                ##  noise:
```

```
                noise = torch.randn(b_size, nz, 1, 1,
device=self.dlstudio.device)
                fakes = netG(noise)
                label.fill_(fake_label)
                ##  The call to fakes.detach() in the next statement
returns a copy of the 'fakes' tensor
                ##  that does not exist in the computational graph.
That is, the call shown below first
                ##  makes a copy of the 'fakes' tensor and then
removes it from the computational graph.
                ##  The original 'fakes' tensor continues to remain in
the computational graph.  This ploy
                ##  ensures that a subsequent call to backward() in
the 3rd statement below would only
                ##  update the netD weights.
                output = netD(fakes.detach()).view(-1)
                lossD_for_fakes = criterion(output, label)
                lossD_for_fakes.backward()
                ##  The following is just for displaying the losses:
                lossD = lossD_for_reals + lossD_for_fakes
                d_losses_per_print_cycle.append(lossD)
                ##  Only the Discriminator weights are incremented:
                optimizerD.step()

                ##  Minimization Part of the Min-Max Objective of Eq.
(3):
                ##
                ##  That brings us to the min part of the max-min
optimization described in Eq. (3) the doc
                ##  section at the beginning of this file.  The min
part requires that we minimize
                ##  "1 - D(G(z))" which, since D is constrained to lie
in the interval (0,1), requires that
                ##  we maximize D(G(z)).  We accomplish that by
applying the Discriminator to the output
                ##  of the Generator and use 1 as the target for each
image:
                netG.zero_grad()
                label.fill_(real_label)
                ##  The following forward prop will compute the
partials wrt the discriminator params also, but
                ##  they will never get used for updating param vals
for two reasons: (1) We call "step()" on
                ##  just optimizerG as shown later below; and (2) We
call "netD.zero_grad()" at the beginning of
                ##  each training cycle.
                output = netD(fakes).view(-1)
                lossG = criterion(output, label)
                g_losses_per_print_cycle.append(lossG)
```

```
                lossG.backward()
                ##  Only the Generator parameters are incremented:
                optimizerG.step()
                if i % 100 == 99:

                    current_time = time.perf_counter()

                    elapsed_time = current_time - start_time

                    mean_D_loss =
torch.mean(torch.FloatTensor(d_losses_per_print_cycle))

                    mean_G_loss =
torch.mean(torch.FloatTensor(g_losses_per_print_cycle))

                    print("[epoch=%d/%d   iter=%4d   elapsed_time=%5d
secs]     mean_D_loss=%7.4f    mean_G_loss=%7.4f" %
                                  ((epoch+1),dlstudio.epochs,
(i+1),elapsed_time,mean_D_loss,mean_G_loss))
                    d_losses_per_print_cycle = []

                    g_losses_per_print_cycle = []

                G_losses.append(lossG.item())

                D_losses.append(lossD.item())

                if (iters % 500 == 0) or ((epoch == dlstudio.epochs-1)
and (i == len(self.train_dataloader)-1)):
                    with torch.no_grad():
                        fake = netG(fixed_noise).detach().cpu()  ##
detach() removes the fake from comp. graph.
                                                                 ##
for creating its CPU compatible version
                    img_list.append(torchvision.utils.make_grid(fake,
padding=1, pad_value=1, normalize=True))
                iters += 1
        #  At the end of training, make plots from the data in
G_losses and D_losses:
        plt.figure(figsize=(10,5))
        plt.title("Generator and Discriminator Loss During Training")

        plt.plot(G_losses,label="G")
        plt.plot(D_losses,label="D")
        plt.xlabel("iterations")
        plt.ylabel("Loss")
        plt.legend()
        plt.savefig(dir_name_for_results +
"/gen_and_disc_loss_training.png")
        plt.show()
```

```
        #  Make an animated gif from the Generator output images
stored in img_list:
        images = []
        for imgobj in img_list:
            img = tvtF.to_pil_image(imgobj)
            images.append(img)
        imageio.mimsave(dir_name_for_results +
"/generation_animation.gif", images, fps=5)
        #  Make a side-by-side comparison of a batch-size sampling of
real images drawn from the
        #  training data and what the Generator is capable of
producing at the end of training:
        real_batch = next(iter(self.train_dataloader))
        real_batch = real_batch[0]
        plt.figure(figsize=(15,15))
        plt.subplot(1,2,1)
        plt.axis("off")
        plt.title("Real Images")

plt.imshow(np.transpose(torchvision.utils.make_grid(real_batch.to(self
.dlstudio.device),
                                               padding=1, pad_value=1,
normalize=True).cpu(),(1,2,0)))
        plt.subplot(1,2,2)

        plt.axis("off")

        plt.title("Fake Images")

        plt.imshow(np.transpose(img_list[-1],(1,2,0)))

        plt.savefig(dir_name_for_results + "/real_vs_fake_images.png")

        plt.show()



    def run_wgan_code(self, dlstudio, critic, generator, results_dir):
        """
        This function is meant for training a CG1-based Critic-
Generator WGAN.   The implementation
        shown uses several programming constructs from the WGAN
implementation at GitHub by the
        original authors of the famous WGAN paper. I have also used
several programming constructs
        from the DCGAN code at PyTorch and GitHub.  Regarding how to
set the parameters of this method,
        see the following script in the "ExamplesAdversarialLearning"
directory of the distribution:

                    wgan_CG1.py
```

```
        """
        dir_name_for_results = results_dir
        if os.path.exists(dir_name_for_results):
            files = glob.glob(dir_name_for_results + "/*")
            for file in files:
                if os.path.isfile(file):
                    os.remove(file)
                else:
                    files = glob.glob(file + "/*")
                    list(map(lambda x: os.remove(x), files))
        else:
            os.mkdir(dir_name_for_results)
        #  Set the number of channels for the 1x1 input noise vectors 
for the Generator:
        nz = 100
        netC = critic.to(self.dlstudio.device)
        netG = generator.to(self.dlstudio.device)
        #  Initialize the parameters of the Critic and the Generator 
networks according to the
        #  definition of the "weights_init()" method:
        netC.apply(self.weights_init)
        netG.apply(self.weights_init)
        #  We will use a the same noise batch to periodically check on 
the progress made for the Generator:
        fixed_noise = torch.randn(self.dlstudio.batch_size, nz, 1, 1, 
device=self.dlstudio.device)
        #  These are for training the Critic, 'one' is for the part of 
the training with actual
        #  training images, and 'minus_one' is for the part based on 
the images produced by the
        #  Generator:
        one = torch.FloatTensor([1]).to(self.dlstudio.device)
        minus_one = torch.FloatTensor([-1]).to(self.dlstudio.device)
        #  Adam optimizers for the Critic and the Generator:
        optimizerC = optim.Adam(netC.parameters(), 
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        optimizerG = optim.Adam(netG.parameters(), 
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        img_list = []
        Gen_losses = []
        Cri_losses = []
        iters = 0
        gen_iterations = 0
        print("\n\nStarting Training Loop.......[Be very patient at 
the beginning since the Critic must separately be taken through a few 
hundred iterations of training before you get to see anything 
displayed in your terminal window.  Depending on your hardware, it may 
take around 5 minutes. Subsequently, each 100 iterations will take 
just a few seconds. ]\n\n")
```

```
        start_time = time.perf_counter()
        dataloader = self.train_dataloader
        clipping_thresh = self.clipping_threshold
        # For each epoch
        for epoch in range(dlstudio.epochs):
            data_iter = iter(dataloader)
            i = 0
            ncritic   = 5
            #  As was stated in the WGAN part of the doc section for
the AdversarialLearning
            #  class at the beginning of this file, a minimization of
the Wasserstein distance between
            #  the distribution that describes the training data and
the distribution that has been learned
            #  so far by the Generator can be translated into a
maximization of the difference of the
            #  average outputs of a 1-Lipschitz function as applied to
the training images and as applied
            #  to the output of the Generator.  LEARNING THIS 1-
Lipschitz FUNCTION IS THE JOB OF THE CRITIC.
            #  Since the Critic and the Generator parameters must be
updated independently, we start by
            #  turning on the "requires_grad" property of the Critic
parameters:
            while i < len(dataloader):
                for p in netC.parameters():
                    p.requires_grad = True
                if gen_iterations < 25 or gen_iterations % 500 == 0:
# the choices 25 and 500 are from WGAN
                    ncritic = 100
                ic = 0
                ##  The inner 'while' loop shown below calculates the
expectations in Eq. (8) in the doc section
                ##  at the beginning of this file:
                while ic < ncritic and i < len(dataloader):
                    ic += 1
                    for p in netC.parameters():
                        p.data.clamp_(-clipping_thresh,
clipping_thresh)
                    ## Training the Critic (Part 1):
                    #  The maximization needed for training the
Critic, as shown in Eq. (8) in the doc section
                    #  at the beginning of this file, consists of two
parts.  The first part involves applying the
                    #  Critic network to just the training images,
with each image subject to a "gradient
                    #  target" of "-1".
                    netC.zero_grad()
```

```
#                         real_images_in_batch =  data_iter.next()
                    real_images_in_batch =  next(data_iter)
                    i += 1
                    real_images_in_batch =
real_images_in_batch[0].to(self.dlstudio.device)
                    #  Need to know how many images we pulled in since
at the tailend of the dataset, the
                    #  number of images may not equal the user-
specified batch size:
                    b_size = real_images_in_batch.size(0)
                    #  Note that a single scalar is produced for all
the data in a batch.  This is probably
                    #  the reason why what the Generator learns is
somewhat fuzzy.
                    critic_for_reals_mean = netC(real_images_in_batch)
                    ## 'minus_one' is the gradient target:
                    critic_for_reals_mean.backward(minus_one)

                    ## Training the Critic (Part 2):
                    #  The second part of Critic training requires
that we apply the Critic to the images
                    #  produced by the Generator for a fresh batch of
input noise vectors. The output of
                    #  the Critic for these images must be subject to
the target "-1".
                    noise = torch.randn(b_size, nz, 1, 1,
device=self.dlstudio.device)
                    fakes = netG(noise)
                    #  Again, a single number is produced for the
whole batch:
                    critic_for_fakes_mean = netC(fakes)
                    ## 'one' is the gradient target:
                    critic_for_fakes_mean.backward(one)
                    wasser_dist = critic_for_reals_mean -
critic_for_fakes_mean
                    loss_critic = critic_for_fakes_mean -
critic_for_reals_mean
                    #  Update the Critic
                    optimizerC.step()

                ## Training the Generator:
                ##   That brings us to the training of the Generator
through the minimization required by the
                ##   minmax objective in Eq. (7) at the beginning of
this file.  To that end, first we must
                ##   turn off the "requires_grad" of the Critic
parameters since the Critic and the Generator
                ##   must be updated independently:
                for p in netC.parameters():
```

```
                    p.requires_grad = False
                netG.zero_grad()
                #  This is again a single scalar based
characterization of the whole batch of the Generator images:
                noise = torch.randn(b_size, nz, 1, 1,
device=self.dlstudio.device)
                fakes = netG(noise)
                critic_for_fakes_mean = netC(fakes)
                loss_gen = critic_for_fakes_mean
                critic_for_fakes_mean.backward(minus_one)

                #  Update the Generator
                optimizerG.step()

                gen_iterations += 1

                if i % (ncritic * 20) == 0:
                    current_time = time.perf_counter()

                    elapsed_time = current_time - start_time

                    print("[epoch=%d/%d   i=%4d   el_time=%5d secs]
loss_critic=%7.4f   loss_gen=%7.4f   Wasserstein_dist=%7.4f" %
(epoch,dlstudio.epochs,i,elapsed_time,loss_critic.data[0],
loss_gen.data[0], wasser_dist.data[0]))
                Gen_losses.append(loss_gen.data[0].item())
                Cri_losses.append(loss_critic.data[0].item())
                #  Get G's output on fixed_noise for the GIF
animation:
                if (iters % 500 == 0) or ((epoch == dlstudio.epochs-1)
and (i == len(dataloader)-1)):
                    with torch.no_grad():

                        fake = netG(fixed_noise).detach().cpu()  ##
detach() removes the fake from comp. graph.
                                                                  ##
for its CPU compatible version
                    img_list.append(torchvision.utils.make_grid(fake,
padding=1, pad_value=1, normalize=True))
                iters += 1


        #  At the end of training, make plots from the data in
Gen_losses and Cri_losses:
        plt.figure(figsize=(10,5))

        plt.title("Generator and Critic Loss During Training")

        plt.plot(Gen_losses,label="G")
```

```
        plt.plot(Cri_losses,label="C")

        plt.xlabel("iterations")

        plt.ylabel("Loss")

        plt.legend()

        plt.savefig(dir_name_for_results +
"/gen_and_critic_loss_training.png")
        plt.show()

        #  Make an animated gif from the Generator output images
stored in img_list:
        images = []

        for imgobj in img_list:

            img = tvtF.to_pil_image(imgobj)

            images.append(img)

        imageio.mimsave(dir_name_for_results +
"/generation_animation.gif", images, fps=5)

        #  Make a side-by-side comparison of a batch-size sampling of
real images drawn from the
        #  training data and what the Generator is capable of
producing at the end of training:
        real_batch = next(iter(dataloader))

        real_batch = real_batch[0]
        plt.figure(figsize=(15,15))

        plt.subplot(1,2,1)

        plt.axis("off")

        plt.title("Real Images")


plt.imshow(np.transpose(torchvision.utils.make_grid(real_batch.to(self
.dlstudio.device),
                                           padding=1, pad_value=1,
normalize=True).cpu(),(1,2,0)))
        plt.subplot(1,2,2)

        plt.axis("off")

        plt.title("Fake Images")
```

```
        plt.imshow(np.transpose(img_list[-1],(1,2,0)))

        plt.savefig(dir_name_for_results + "/real_vs_fake_images.png")

        plt.show()



    def run_wgan_with_gp_code(self, dlstudio, critic, generator,
results_dir):
        """
        This function is meant for training a CG2-based Critic-
Generator WGAN. Regarding how
        to set the parameters of this method, see the following script
in the
        "ExamplesAdversarialLearning" directory of the distribution:

                     wgan_with_gp_CG2.py
        """
        dir_name_for_results = results_dir
        if os.path.exists(dir_name_for_results):
            files = glob.glob(dir_name_for_results + "/*")
            for file in files:
                if os.path.isfile(file):
                    os.remove(file)
                else:
                    files = glob.glob(file + "/*")
                    list(map(lambda x: os.remove(x), files))
        else:
            os.mkdir(dir_name_for_results)
        #  Set the number of channels for the 1x1 input noise vectors
for the Generator:
        nz = 100
        netC = critic.to(self.dlstudio.device)
        netG = generator.to(self.dlstudio.device)
        #  Initialize the parameters of the Critic and the Generator
networks according to the
        #  definition of the "weights_init()" method:
        netC.apply(self.weights_init)
        netG.apply(self.weights_init)
        #  We will use a the same noise batch to periodically check on
the progress made for the Generator:
        fixed_noise = torch.randn(self.dlstudio.batch_size, nz, 1, 1,
device=self.dlstudio.device)
        #  These are for training the Critic, 'one' is for the part of
the training with actual
        #  training images, and 'minus_one' is for the part based on
the images produced by the
        #  Generator:
        one = torch.FloatTensor([1]).to(self.dlstudio.device)
```

```
        minus_one = torch.FloatTensor([-1]).to(self.dlstudio.device)
        #  Adam optimizers for the Critic and the Generator:
        optimizerC = optim.Adam(netC.parameters(), 
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        optimizerG = optim.Adam(netG.parameters(), 
lr=dlstudio.learning_rate, betas=(self.beta1, 0.999))
        img_list = []
        Gen_losses = []
        Cri_losses = []
        iters = 0
        gen_iterations = 0
        start_time = time.perf_counter()
        dataloader = self.train_dataloader
        # For each epoch
        for epoch in range(dlstudio.epochs):
            data_iter = iter(dataloader)
            i = 0
            ncritic   = 5
            #  In this version of WGAN training, we enforce the 1-
Lipschitz condition on the function
            #  being learned by the Critic by requiring that the 
partial derivatives of the output of
            #  the Critic with respect to its input equal one in 
magnitude. This is referred as imposing
            #  a Gradient Penalty on the learning by the Critic.  As 
in the previous training
            #  function, we start by turning on the "requires_grad" 
property of the Critic parameters:
            while i < len(dataloader):
                for p in netC.parameters():
                    p.requires_grad = True
                ic = 0
                while ic < ncritic and i < len(dataloader):
                    ic += 1
                    #  The first two parts of what it takes to train 
the Critic are the same as for
                    #  a regular WGAN.  We want to train the Critic to 
recognize the training images and,
                    #  at the same time, the Critic should try to not 
believe the output of the Generator.
                    netC.zero_grad()

#                         real_images_in_batch =  data_iter.next()
                    real_images_in_batch =  next(data_iter)
                    i += 1
                    real_images_in_batch = 
real_images_in_batch[0].to(self.dlstudio.device)
                    #  Need to know how many images we pulled in since 
at the tailend of the dataset, the
```

```
                    #  number of images may not equal the user-
specified batch size:
                    b_size = real_images_in_batch.size(0)
                    #  Note that a single scalar is produced for all
the data in a batch.
                    critic_for_reals_mean = netC(real_images_in_batch)
## this is a batch based mean
                    #  The gradient target is 'minus_one'.  Note that
the gradient here is one of output of
                    #  the network with respect to the learnable
parameters:
                    critic_for_reals_mean.backward(minus_one)
                    #  The second part of Critic training requires
that we apply the Critic to the images
                    #  produced by the Generator from a fresh batch of
input noise vectors.
                    noise = torch.randn(b_size, nz, 1, 1,
device=self.dlstudio.device)
                    fakes = netG(noise)
                    #  Again, a single number is produced for the
whole batch:
                    critic_for_fakes_mean = netC(fakes.detach())  ##
detach() returns a copy of the 'fakes' tensor that has
                                                                  ##
been removed from the computational graph. This ensures
                                                                  ##
that a subsequent call to backward() will only update the Critic
                    #  The gradient target is 'one'.  Note that the
gradient here is one of output of
                    #  the network with respect to the learnable
parameters:
                    critic_for_fakes_mean.backward(one)
                    #  For the third part of Critic training, we need
to first estimate the Gradient Penalty
                    #  of the function being learned by the Critics
with respect to the input to the function.
                    gradient_penalty =
self.calc_gradient_penalty(netC, real_images_in_batch, fakes)
                    gradient_penalty.backward()
                    loss_critic = critic_for_fakes_mean -
critic_for_reals_mean + gradient_penalty
                    wasser_dist = critic_for_reals_mean -
critic_for_fakes_mean
                    #  Update the Critic
                    optimizerC.step()

                #  That brings us to the training of the Generator.
First we must turn off the "requires_grad"
                #  of the Critic parameters since the Critic and the
```

```
Generator are to be updated independently:
                for p in netC.parameters():
                    p.requires_grad = False
                netG.zero_grad()
                #  This is again a single scalar based
characterization of the whole batch of the Generator images:
                noise = torch.randn(b_size, nz, 1, 1,
device=self.dlstudio.device)
                fakes = netG(noise)
                critic_for_fakes_mean = netC(fakes)
                loss_gen = critic_for_fakes_mean
                #  The gradient target is 'minus_one'.  Note that the
gradient here is one of output of the network
                #  with respect to the learnable parameters:
                loss_gen.backward(minus_one)
                #  Update the Generator
                optimizerG.step()

                gen_iterations += 1
                if i % (ncritic * 20) == 0:
                    current_time = time.perf_counter()

                    elapsed_time = current_time - start_time

                    print("[epoch=%d/%d   i=%4d   el_time=%5d secs]
loss_critic=%7.4f   loss_gen=%7.4f   Wasserstein_dist=%7.4f" %
(epoch+1,dlstudio.epochs,i,elapsed_time,loss_critic.data[0],
loss_gen.data[0], wasser_dist.data[0]))
                Gen_losses.append(loss_gen.data[0].item())
                Cri_losses.append(loss_critic.data[0].item())
                #  Get G's output on fixed_noise for the GIF
animation:
                if (iters % 500 == 0) or ((epoch == dlstudio.epochs-1)
and (i == len(self.train_dataloader)-1)):
                    with torch.no_grad():

                        fake = netG(fixed_noise).detach().cpu()  ##
detach() removes the fake from comp. graph
                                                                  ## in
order to produce a CPU compatible tensor
                    img_list.append(torchvision.utils.make_grid(fake,
padding=1, pad_value=1, normalize=True))
                iters += 1


        #  At the end of training, make plots from the data in
Gen_losses and Cri_losses:
        plt.figure(figsize=(10,5))

        plt.title("Generator and Critic Loss During Training")
```

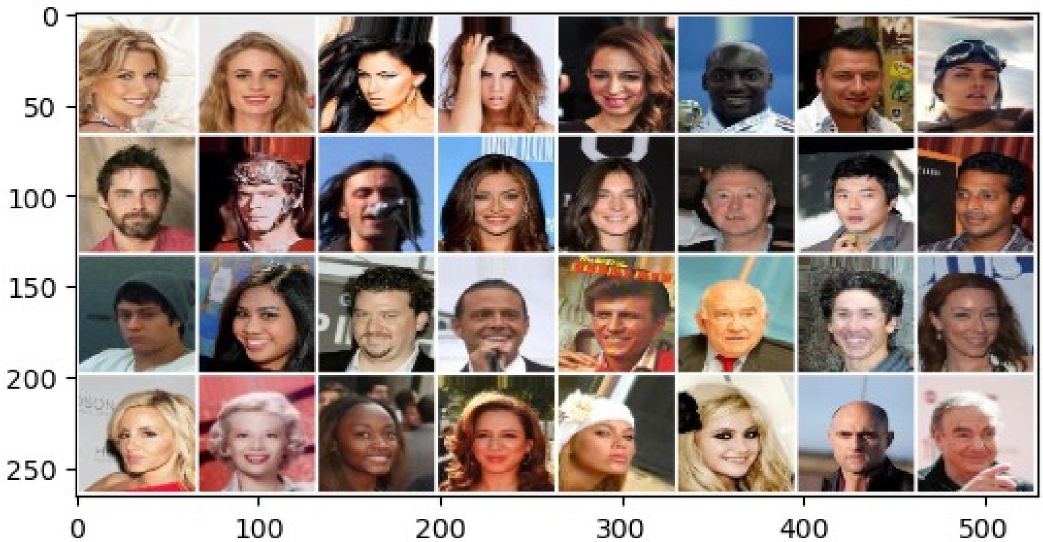
```
        plt.plot(Gen_losses,label="G")

        plt.plot(Cri_losses,label="C")

        plt.xlabel("iterations")

        plt.ylabel("Loss")

        plt.legend()

        plt.savefig(dir_name_for_results +
"/gen_and_critic_loss_training.png")
        plt.show()

        #  Make an animated gif from the Generator output images
stored in img_list:
        images = []

        for imgobj in img_list:

            img = tvtF.to_pil_image(imgobj)

            images.append(img)

        imageio.mimsave(dir_name_for_results +
"/generation_animation.gif", images, fps=5)

        #  Make a side-by-side comparison of a batch-size sampling of
real images drawn from the
        #  training data and what the Generator is capable of
producing at the end of training:
        real_batch = next(iter(self.train_dataloader))

        real_batch = real_batch[0]
        plt.figure(figsize=(15,15))

        plt.subplot(1,2,1)

        plt.axis("off")

        plt.title("Real Images")


plt.imshow(np.transpose(torchvision.utils.make_grid(real_batch.to(self
.dlstudio.device),
                                           padding=1, pad_value=1,
normalize=True).cpu(),(1,2,0)))
        plt.subplot(1,2,2)

        plt.axis("off")
```

```
        plt.title("Fake Images")

        plt.imshow(np.transpose(img_list[-1],(1,2,0)))

        plt.savefig(dir_name_for_results + "/real_vs_fake_images.png")

        plt.show()



    def save_model(self, model):
        '''
        Save the trained model to a disk file
        '''
        torch.save(model.state_dict(),
self.dl_studio.path_saved_model)
```

## 1.2 Training curves

```
# the code below is mainly borrowed from DLSudio-2.5.2


import random
import numpy
import torch
import cv2

seed = 0
random.seed(seed)
torch.manual_seed(seed)
torch.cuda.manual_seed(seed)
numpy.random.seed(seed)
torch.backends.cudnn.deterministic=True
torch.backends.cudnn.benchmarks=False
os.environ['PYTHONHASHSEED'] = str(seed)


dls = DLStudio(
                  dataroot = "./Supplementary/celeba_dataset_64x64/",

                  # dataroot = "./dataGAN/PurdueShapes5GAN/multiobj/",


                  image_size = [64,64],

                  path_saved_model = "./saved_model",

                  learning_rate = 2e-4,     ## <== try smaller value
if mode collapse
                  # learning_rate = 1e-5,     ## <== the output is
```

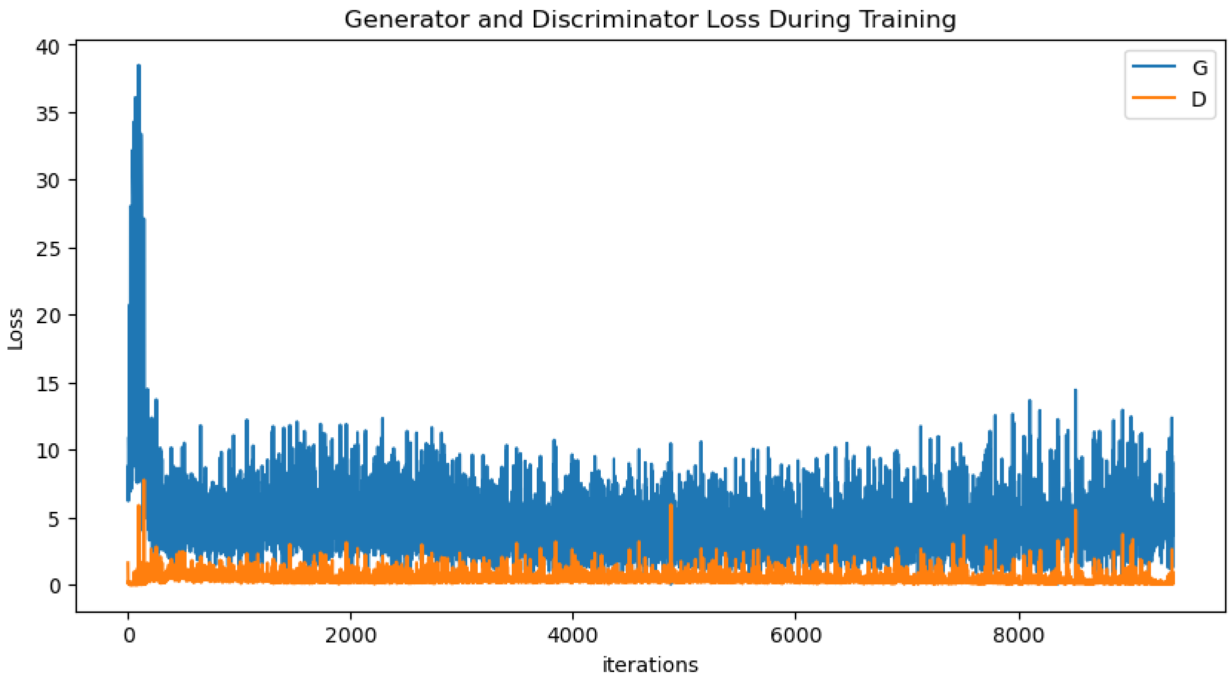
```
super bad
                  epochs = 30,
                  batch_size = 32,

                  use_gpu = True,

              )

dcgan = MyAdversarialLearning(
                  dlstudio = dls,
                  ngpu = 1,
                  latent_vector_size = 100,
                  beta1 = 0.5,                           ## for the
Adam optimizer
              )

discriminator =  dcgan.DiscriminatorDG2()
generator =  dcgan.GeneratorDG2()



dcgan.set_dataloader()

dcgan.show_sample_images_from_dataset(dls)

dcgan.run_gan_code(dls, discriminator=discriminator,
generator=generator, results_dir="results_DG2")

# save model
torch.save(generator.state_dict(), "./generator.pth")
torch.save(discriminator.state_dict(), "./discriminator.pth")
```

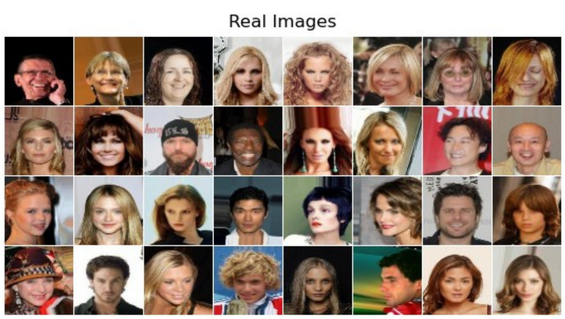


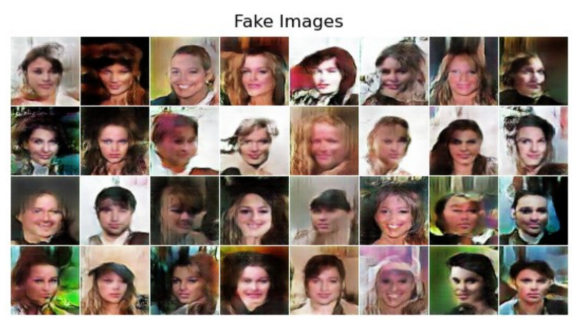

```
Starting Training Loop...

[epoch=1/30   iter= 100   elapsed_time=   27 secs]     mean_D_loss=
0.2562    mean_G_loss=21.0271
[epoch=1/30   iter= 300   elapsed_time=   67 secs]     mean_D_loss=
0.7281    mean_G_loss= 9.4440
[epoch=2/30   iter= 100   elapsed_time=   99 secs]     mean_D_loss=
0.7063    mean_G_loss= 4.5943
[epoch=2/30   iter= 300   elapsed_time=  139 secs]     mean_D_loss=
0.7870    mean_G_loss= 4.5438
[epoch=3/30   iter= 100   elapsed_time=  172 secs]     mean_D_loss=
0.6686    mean_G_loss= 4.4085
[epoch=3/30   iter= 300   elapsed_time=  212 secs]     mean_D_loss=
0.7281    mean_G_loss= 4.5149
[epoch=4/30   iter= 100   elapsed_time=  245 secs]     mean_D_loss=
0.6891    mean_G_loss= 4.7506
[epoch=4/30   iter= 300   elapsed_time=  285 secs]     mean_D_loss=
0.6342    mean_G_loss= 4.7358
[epoch=5/30   iter= 100   elapsed_time=  319 secs]     mean_D_loss=
0.5143    mean_G_loss= 4.9340
[epoch=5/30   iter= 300   elapsed_time=  358 secs]     mean_D_loss=
0.4951    mean_G_loss= 5.1045
[epoch=6/30   iter= 100   elapsed_time=  392 secs]     mean_D_loss=
0.4403    mean_G_loss= 4.9777
[epoch=6/30   iter= 300   elapsed_time=  434 secs]     mean_D_loss=
0.5422    mean_G_loss= 5.0491
[epoch=7/30   iter= 100   elapsed_time=  490 secs]     mean_D_loss=
0.4655    mean_G_loss= 5.2195
[epoch=7/30   iter= 300   elapsed_time=  728 secs]     mean_D_loss=
```

```
0.5138    mean_G_loss= 4.8875
[epoch=8/30   iter= 100   elapsed_time=  871 secs]     mean_D_loss=
0.4783    mean_G_loss= 5.1607
[epoch=8/30   iter= 300   elapsed_time= 1110 secs]     mean_D_loss=
0.4826    mean_G_loss= 4.8877
[epoch=9/30   iter= 100   elapsed_time= 1258 secs]     mean_D_loss=
0.4843    mean_G_loss= 4.6394
[epoch=9/30   iter= 300   elapsed_time= 1497 secs]     mean_D_loss=
0.5271    mean_G_loss= 4.7227
[epoch=10/30   iter= 100   elapsed_time= 1646 secs]     mean_D_loss=
0.6045    mean_G_loss= 4.7244
[epoch=10/30   iter= 300   elapsed_time= 1885 secs]     mean_D_loss=
0.5134    mean_G_loss= 4.3287
[epoch=11/30   iter= 100   elapsed_time= 2033 secs]     mean_D_loss=
0.5230    mean_G_loss= 4.2763
[epoch=11/30   iter= 300   elapsed_time= 2272 secs]     mean_D_loss=
0.5189    mean_G_loss= 4.1503
[epoch=12/30   iter= 100   elapsed_time= 2421 secs]     mean_D_loss=
0.5641    mean_G_loss= 4.2605
[epoch=12/30   iter= 300   elapsed_time= 2659 secs]     mean_D_loss=
0.5540    mean_G_loss= 4.0672
[epoch=13/30   iter= 100   elapsed_time= 2809 secs]     mean_D_loss=
0.4877    mean_G_loss= 4.1415
[epoch=13/30   iter= 300   elapsed_time= 3048 secs]     mean_D_loss=
0.5645    mean_G_loss= 4.0690
[epoch=14/30   iter= 100   elapsed_time= 3198 secs]     mean_D_loss=
0.4757    mean_G_loss= 3.8550
[epoch=14/30   iter= 300   elapsed_time= 3436 secs]     mean_D_loss=
0.5281    mean_G_loss= 4.0452
[epoch=15/30   iter= 100   elapsed_time= 3586 secs]     mean_D_loss=
0.4668    mean_G_loss= 4.0376
[epoch=15/30   iter= 300   elapsed_time= 3825 secs]     mean_D_loss=
0.5711    mean_G_loss= 4.0152
[epoch=16/30   iter= 100   elapsed_time= 3974 secs]     mean_D_loss=
0.4843    mean_G_loss= 4.0258
[epoch=16/30   iter= 300   elapsed_time= 4213 secs]     mean_D_loss=
0.5655    mean_G_loss= 4.0645
[epoch=17/30   iter= 100   elapsed_time= 4363 secs]     mean_D_loss=
0.5066    mean_G_loss= 4.0284
[epoch=17/30   iter= 300   elapsed_time= 4601 secs]     mean_D_loss=
0.5583    mean_G_loss= 4.0195
[epoch=18/30   iter= 100   elapsed_time= 4751 secs]     mean_D_loss=
0.5250    mean_G_loss= 3.8803
[epoch=18/30   iter= 300   elapsed_time= 4990 secs]     mean_D_loss=
0.4980    mean_G_loss= 3.9769
[epoch=19/30   iter= 100   elapsed_time= 5140 secs]     mean_D_loss=
0.4769    mean_G_loss= 4.0000
[epoch=19/30   iter= 300   elapsed_time= 5379 secs]     mean_D_loss=
0.5529    mean_G_loss= 4.0067
```

```
[epoch=20/30   iter= 100   elapsed_time= 5529 secs]     mean_D_loss=
0.4645    mean_G_loss= 3.9217
[epoch=20/30   iter= 300   elapsed_time= 5768 secs]     mean_D_loss=
0.4621    mean_G_loss= 3.9671
[epoch=21/30   iter= 100   elapsed_time= 5918 secs]     mean_D_loss=
0.4589    mean_G_loss= 4.0622
[epoch=21/30   iter= 300   elapsed_time= 6157 secs]     mean_D_loss=
0.5181    mean_G_loss= 4.2106
[epoch=22/30   iter= 100   elapsed_time= 6306 secs]     mean_D_loss=
0.3586    mean_G_loss= 4.1458
[epoch=22/30   iter= 300   elapsed_time= 6545 secs]     mean_D_loss=
0.4391    mean_G_loss= 4.3382
[epoch=23/30   iter= 100   elapsed_time= 6695 secs]     mean_D_loss=
0.6453    mean_G_loss= 4.4343
[epoch=23/30   iter= 300   elapsed_time= 6934 secs]     mean_D_loss=
0.4301    mean_G_loss= 4.1801
[epoch=24/30   iter= 100   elapsed_time= 7084 secs]     mean_D_loss=
0.4513    mean_G_loss= 4.4192
[epoch=24/30   iter= 300   elapsed_time= 7323 secs]     mean_D_loss=
0.4361    mean_G_loss= 4.3060
[epoch=25/30   iter= 100   elapsed_time= 7474 secs]     mean_D_loss=
0.4157    mean_G_loss= 4.2367
[epoch=25/30   iter= 300   elapsed_time= 7713 secs]     mean_D_loss=
0.4173    mean_G_loss= 4.4900
[epoch=26/30   iter= 100   elapsed_time= 7863 secs]     mean_D_loss=
0.3061    mean_G_loss= 4.4125
[epoch=26/30   iter= 300   elapsed_time= 8102 secs]     mean_D_loss=
0.4041    mean_G_loss= 4.6156
[epoch=27/30   iter= 100   elapsed_time= 8252 secs]     mean_D_loss=
0.4008    mean_G_loss= 4.6062
[epoch=27/30   iter= 300   elapsed_time= 8491 secs]     mean_D_loss=
0.3642    mean_G_loss= 4.5314
[epoch=28/30   iter= 100   elapsed_time= 8641 secs]     mean_D_loss=
0.4097    mean_G_loss= 4.5341
[epoch=28/30   iter= 300   elapsed_time= 8880 secs]     mean_D_loss=
0.3419    mean_G_loss= 4.5949
[epoch=29/30   iter= 100   elapsed_time= 9029 secs]     mean_D_loss=
0.3106    mean_G_loss= 4.6599
[epoch=29/30   iter= 300   elapsed_time= 9268 secs]     mean_D_loss=
0.4008    mean_G_loss= 4.7462
[epoch=30/30   iter= 100   elapsed_time= 9418 secs]     mean_D_loss=
0.3484    mean_G_loss= 4.7665
[epoch=30/30   iter= 300   elapsed_time= 9657 secs]     mean_D_loss=
0.1682    mean_G_loss= 4.6479
```




```
# use genertor to generate images and save them for further use
gen = generator.to(dls.device)
gen.eval()
with torch.no_grad():

    # we need 1024 in total, so we need loop 32 times
    for j in range(32):
        noise = torch.randn(32, 100, 1, 1, device=dls.device)
        fake = gen(noise).detach().cpu() # shape: (32, C, H, W)

        # save them in output dir as png files
        os.makedirs("Generator_Output", exist_ok=True)

        for i in range(fake.size(0)): # 32 in this case
            img = fake[i]  # shape: (C, H, W)
            img = img.numpy().transpose(1, 2, 0)  # to (H, W, C)

            img = (img + 1) / 2.0  # Normalize from [-1,1] → [0,1]
            img = np.clip(img * 255.0, 0, 255)  # Scale to [0,255]
```

```
            img = img.astype(np.uint8)

            # Convert from RGB to BGR (OpenCV uses BGR format)
            img = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)


            cv2.imwrite(f"Generator_Output/fake_{j*32 + i}.jpg", img)
```

# 2 Diffusion

## 2.1 Generate Images

Since my personal laptop GPU isn't powerful enough to run multiple epochs of diffusion training with a batch size of 32, I am using the provided weights and skipping the execution of RunCodeForDiffusion.py.

```
# the code below is mainly borrowed from DLSudio-2.5.2
import numpy as np


GenerativeDiffusion_dir = os.path.join(DLStudio_dir,
"GenerativeDiffusion")
sys.path.append(GenerativeDiffusion_dir)

from GenerativeDiffusion import *

gauss_diffusion   =  GaussianDiffusion(
                        num_diffusion_timesteps = 1000,
                    )


network =  UNetModel(
                       in_channels=3,
                       model_channels   =  128,
                       out_channels     =  3,
                       num_res_blocks   =  2,
                       attention_resolutions =  (4, 8),
## for 64x64 images
                       channel_mult     =    (1, 2, 3, 4),
## for 64x64 images
                       num_heads        =    1,
                       attention        =    True             ## <<<
Must be the same as for RunCodeForDiffusion.py
#                       attention        =    False            ## <<<
Must be the same as for RunCodeForDiffusion.py

                     )
```

```
top_level = GenerativeDiffusion(
                        gen_new_images        =        True,
                        image_size            =        64,
                        num_channels          =        128,
                        ema_rate              =        0.9999,
                        diffusion = gauss_diffusion,
                        network = network,
                        ngpu = 1,
                        path_saved_model = "./RESULTS",
                        clip_denoised=True,
                        num_samples=1024,
                        batch_size_image_generation=8,
             )


model_path = "Supplementary/diffusion.pt"


network.load_state_dict( torch.load(model_path) )

network.to(top_level.device)
network.eval()

print("sampling...")
all_images = []

while len(all_images) * top_level.batch_size_image_generation <
top_level.num_samples:
    sample = gauss_diffusion.p_sampler_for_image_generation(
        network,
        (top_level.batch_size_image_generation, 3,
top_level.image_size, top_level.image_size),
        device = top_level.device,
        clip_denoised = top_level.clip_denoised,
    )
    sample = ((sample + 1) * 127.5).clamp(0, 255).to(torch.uint8)
    sample = sample.permute(0, 2, 3, 1)
    sample = sample.contiguous()
    gathered_samples = [sample]
    all_images.extend([sample.cpu().numpy() for sample in
gathered_samples])
    print(f"created {len(all_images) *
top_level.batch_size_image_generation} samples")



arr = np.concatenate(all_images, axis=0)
arr = arr[: top_level.num_samples]
```

```
shape_str = "x".join([str(x) for x in arr.shape])

out_path = os.path.join("./", f"samples_{shape_str}.npz")

np.savez(out_path, arr)

print("image generation completed")

from PIL import Image
import os
import numpy as np
import glob
import matplotlib.pyplot as plt
import torch
import torchvision



npz_archive = "./samples_1024x64x64x3.npz"        ##  You must change
this as needed.  The first number, 32,
                                                      ##  is the
batch-size used for sampling a checkpoint.  It
                                                      ##  is set in
the script GenerateNewImageSamples.py.
                                                      ##
                                                      ##  In our case,
an npz archive is a dict with a single
                                                      ##  'key-value'
pair.  The name of the 'key' is 'arr_0'.
                                                      ##  And the
shape of the 'value' will be the shape of the
                                                      ##  ndarray that
stores the generated images. For the example
                                                      ##  shown, the
shape of the value is (32,64,64,3)
visualization_dir  =  "Diffusion_Output"
# image_display_size = (256,256)


if os.path.exists(visualization_dir):
    files = glob.glob(visualization_dir + "/*")
    for file in files:
        if os.path.isfile(file):
            os.remove(file)
else:
    os.mkdir(visualization_dir)

data = np.load(npz_archive)

for i, arr in enumerate(data['arr_0']):
```

```
    img = Image.fromarray( arr )
    # img = img.resize( image_display_size )
    img.save( f"Diffusion_Output/test_{i}.jpg" )
```

# 3 FID score

## 3.1 Display 4x4(16) images generated by GAN

```
from PIL import Image
def display_images(img_dir):
    img_files = os.listdir(img_dir)
    img_files = img_files[:16] # get the first 16 images


    fig, axes = plt.subplots(4, 4, figsize=(10, 10))
    fig.suptitle(img_dir)

    for axis, img_file in zip(axes.flatten(), img_files): #
axes.flatten() → [ax0, ax1, ..., ax15]. zip → [(ax0, img0), (ax1,
img1), ...]
        img_path = os.path.join(img_dir, img_file)
        img = Image.open(img_path)
        axis.imshow(img)
        axis.axis('off')

    plt.tight_layout()
    plt.show()

img_dir = "Generator_Output"
display_images(img_dir)
```

Generator_Output

## 3.2 Display 4x4(16) images generated by Diffusion

```
img_dir = "Diffusion_Output\Diffusion_Output"
display_images(img_dir)
```

Diffusion_Output\Diffusion_Output

## 3.3 GAN FID

```
from pytorch_fid.fid_score import calculate_activation_statistics,
calculate_frechet_distance
from pytorch_fid.inception import InceptionV3


device = 'cuda' if torch.cuda.is_available() else 'cpu'


def calculate_fid(real_img_dir, fake_img_dir):
    dims = 2048
```

```
    block_idx = InceptionV3.BLOCK_INDEX_BY_DIM[dims]
    model = InceptionV3([block_idx]).to(device)

    # make images in the directory as numpy arrays
    fake_img_files = os.listdir(fake_img_dir)
    real_img_files = os.listdir(real_img_dir)

    fake_paths = [os.path.join(fake_img_dir, img_file) for img_file in
fake_img_files]
    real_paths = [os.path.join(real_img_dir, img_file) for img_file in
real_img_files]

    m1, s1 = calculate_activation_statistics(real_paths, model,
device=device)
    m2, s2 = calculate_activation_statistics(fake_paths, model,
device=device)

    fid_value = calculate_frechet_distance(m1, s1, m2, s2)

    return fid_value


fake_img_dir = "Generator_Output"
real_img_dir =
"Supplementary/celeba_dataset_64x64/celeba_dataset_64x64"



# # calculate FID score
fid_value = calculate_fid(real_img_dir, fake_img_dir)
print(f"FID score of GAN: {fid_value}")

Using device: cuda
FID score of GAN: 66.20835395075642
```

## 3.4 Diffusion FID

```
fake_img_dir = "Diffusion_Output"

fid_value = calculate_fid(real_img_dir, fake_img_dir)
print(f"FID score of Diffusion: {fid_value}")

FID score of Diffusion: 55.308944348883074
```

## - Qualitative Evaluation:

For the GAN-generated **(Generator)** images, there is a noticeable lack of detail — textures appear vague and poorly defined. Additionally, the facial proportions are often inconsistent, with some features being unnaturally placed or distorted. However, in my generated dataset, I did not observe signs of mode collapse — the samples appear diverse and vary across different runs.

In contrast, the images generated by the Diffusion model **(p-chain)** are significantly sharper and more realistic. The textures are more consistent and natural-looking, and facial features are generally well-structured and proportionally accurate. Overall, the visual quality of the Diffusion outputs is noticeably higher than that of the GAN.

One reason Diffusion models tend to outperform GANs is due to the fundamental difference in how they are trained and how they generate data. GANs start from Gaussian noise and learn a direct mapping to output images in a single forward pass, which makes training unstable and prone to issues like mode collapse or artifacts. Diffusion models, on the other hand, follow a gradual denoising process: they start with pure noise and iteratively remove noise over many steps to generate a high-quality image. This slow, step-by-step generation allows diffusion models to capture fine-grained details and complex data distributions more effectively.

Architecturally, GANs rely heavily on the adversarial setup between a generator and a discriminator, which often creates a delicate balance that's hard to maintain. Diffusion models, in contrast, are trained with a denoising score matching objective and don’t rely on adversarial loss — making training more stable and less sensitive to hyperparameters.

### - Quantitative Evaluation:

| | GAN | Diffusion |
|---|---|---|
| FID Score | 66.2 | 55.3 |

Although visually Diffusion has better results, the Diffusion model scored 55.3 in FID, while the GAN scored 66.2. I think the reason for this discrepancy lies in how FID evaluates similarity to the real data distribution. Despite the higher visual quality of Diffusion samples, they may introduce subtle distributional shifts or over-smooth textures that deviate statistically from the real images, which can affect the FID score. On the other hand, GANs — while sometimes producing artifacts or less detailed images — might still align more closely with the overall statistical moments (mean and covariance) of the dataset, thus receiving a slightly better FID score. This highlights a known limitation of FID: it doesn't always perfectly correlate with human perception of image quality. Therefore, a combination of both qualitative and quantitative evaluation provides a more complete picture of generative model performance.

# Finetune GAN

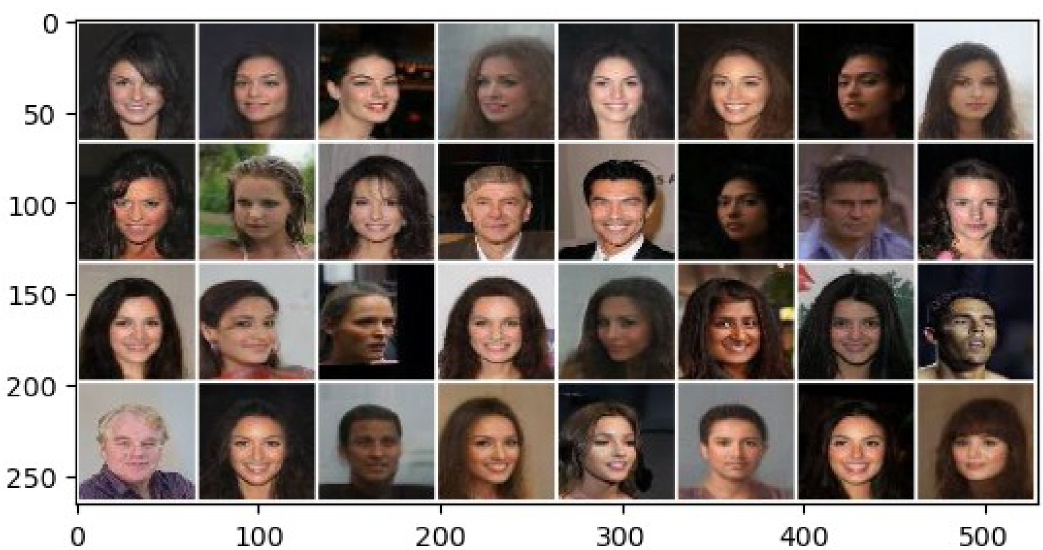
## 4.1 Training curves

```
# the code below is mainly borrowed from DLSudio-2.5.2


import random
import numpy
import torch
import cv2

seed = 0
random.seed(seed)
torch.manual_seed(seed)
```

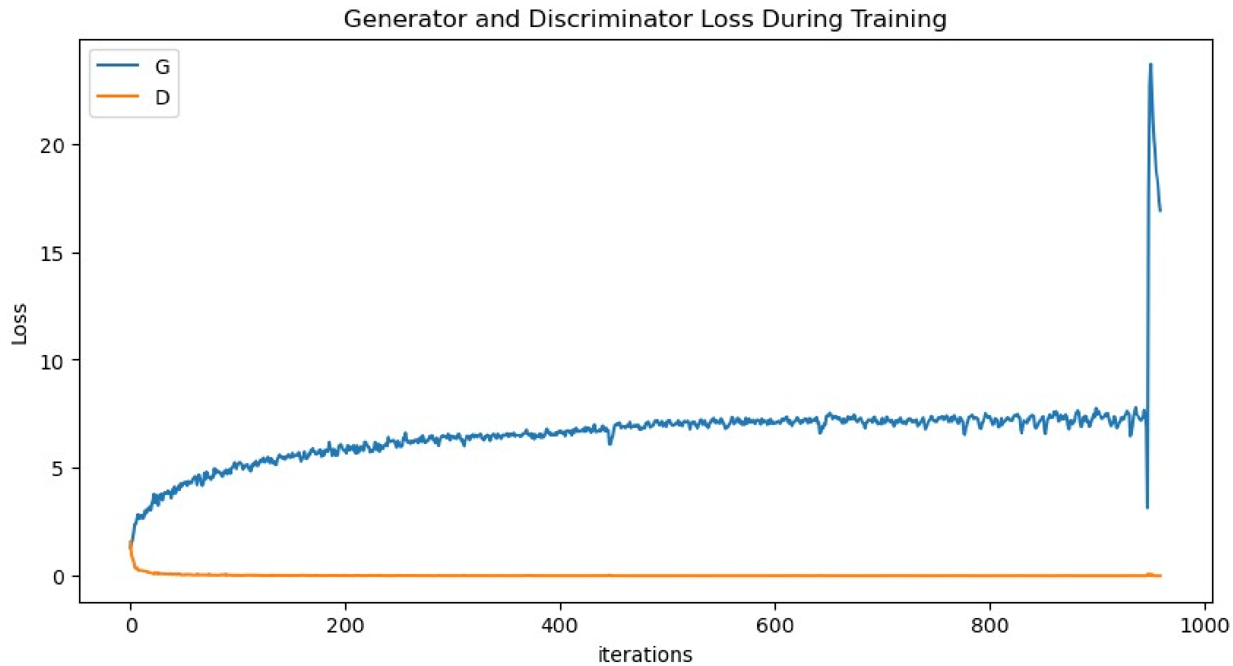
```
torch.cuda.manual_seed(seed)
numpy.random.seed(seed)
torch.backends.cudnn.deterministic=True
torch.backends.cudnn.benchmarks=False
os.environ['PYTHONHASHSEED'] = str(seed)


dls = DLStudio(
                  dataroot = "./Diffusion_Output/",

                  image_size = [64,64],

                  path_saved_model = "./saved_model",
                #   learning_rate = 2e-4,     ## <== mode collapse
                  # learning_rate = 2e-5,     ## <== mode collapse
                  learning_rate = 1e-5,     ## <== mode collapse
                  epochs = 30,
                  batch_size = 32,

                  use_gpu = True,

              )

dcgan = MyAdversarialLearning(
                  dlstudio = dls,
                  ngpu = 1,
                  latent_vector_size = 100,
                  beta1 = 0.5,                           ## for the
Adam optimizer
              )

discriminator =  dcgan.DiscriminatorDG2()

# using the pretrained model make the discriminator too strong, it
gives very harsh gradients to the generator.
# discriminator.load_state_dict(torch.load("./discriminator.pth"))
# discriminator.to(dls.device)

generator =  dcgan.GeneratorDG2()
generator.load_state_dict(torch.load("./generator.pth"))
generator.to(dls.device)



dcgan.set_dataloader()

dcgan.show_sample_images_from_dataset(dls)

dcgan.run_gan_code(dls, discriminator=discriminator,
generator=generator, results_dir="results_DG2_finetuned")
```

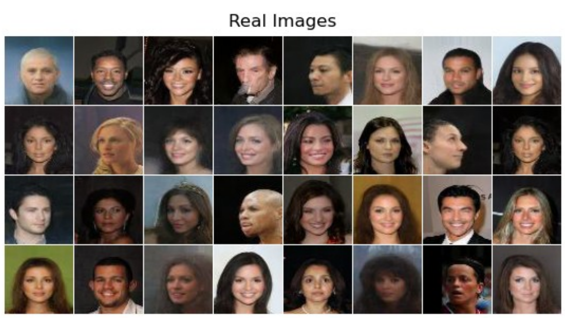
```python
# save model
torch.save(generator.state_dict(), "./generator_finetuned.pth")
torch.save(discriminator.state_dict(),
"./discriminator_finetuned.pth")
```

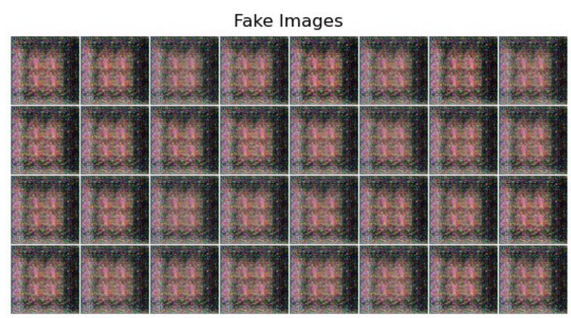
```
C:\Users\alanc\AppData\Local\Temp\ipykernel_11212\377586184.py:42:
FutureWarning: You are using `torch.load` with `weights_only=False`
(the current default value), which uses the default pickle module
implicitly. It is possible to construct malicious pickle data which
will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  generator.load_state_dict(torch.load("./generator.pth"))
```




```
Starting Training Loop...
```




## 4.2 Visual observations of finetuned GAN against GAN

The outputs of the fine-tuned GAN show classic mode collapse — every generated image is an identical, abstract pattern that does not resemble human faces. Despite experimenting with various learning rates and even removing the pretrained discriminator (allowing it to learn from scratch), mode collapse persisted across runs.

In fact, the performance of the fine-tuned GAN is worse than the original GAN. This degradation likely stems from the fact that the fine-tuned model was trained on diffusion-generated images, which, while high in visual quality, are still synthetic. These images can carry subtle biases, overly smooth textures, or a lack of true diversity compared to real-world data, leading to poor generalization when used to train a GAN.

## 4.3 Visual observations of finetuned GAN against Diffusion

The diffusion model continues to produce sharp, diverse, and realistic human faces, while the fine-tuned GAN fails to do so. This contrast emphasizes how much better the diffusion model captures data distributions, even compared to a GAN trained (or fine-tuned) on diffusion outputs.

## 4.4 Display 4x4(16) images generated by finetuned GAN

```python
# use genertor to generate images and save them for further use
gen = generator.to(dls.device)
gen.eval()
with torch.no_grad():
    # we need 1024 in total, so we need loop 32 times
    for j in range(32):
        noise = torch.randn(32, 100, 1, 1, device=dls.device)
        fake = gen(noise).detach().cpu() # shape: (32, C, H, W)

        # save them in output dir as png files
        os.makedirs("Generator_finetuned_Output", exist_ok=True)

        for i in range(fake.size(0)): # 32 in this case
            img = fake[i]  # shape: (C, H, W)
            img = img.numpy().transpose(1, 2, 0)  # to (H, W, C)

            img = (img + 1) / 2.0  # Normalize from [-1,1] → [0,1]
            img = np.clip(img * 255.0, 0, 255)  # Scale to [0,255]
            img = img.astype(np.uint8)

            # Convert from RGB to BGR (OpenCV uses BGR format)
            img = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)


            cv2.imwrite(f"Generator_finetuned_Output/fake_{j*32 +
i}.jpg", img)


img_dir = "Generator_finetuned_Output"
display_images(img_dir)
```


- Discuss how training with diffusion-generated images affects the GANs performance.

Training a GAN on diffusion-generated images instead of real data significantly hurts performance. Visually, the generator fails to capture human-like structure and instead learns to produce repetitive, abstract patterns — an indication that it's not extracting meaningful or generalizable features. The root issue is **distribution mismatch**.

Diffusion-generated images, though realistic-looking, are still synthetic and may contain distributional artifacts, lack the complex diversity found in natural data, and be too smooth or consistent, offering fewer cues for the discriminator

As a result, the discriminator struggles to learn meaningful boundaries, weakening the training signal.Additionally, the generator overfits to superficial patterns present in the diffusion images. Finally, the model enters mode collapse, repeatedly generating the same output.