Lab 07: Generative Adversarial Networks (GANs)

In this lab, we will develop several basic GANs and experiment with them.

Some of the information in this lab is based on material from Building Basic Generative Adversarial Networks (GANs) in Coursera.

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Task 1.

Reproduce the vanilla GAN and DCGAN results on MNIST and CIFAR.

Get the training and test loss for the generator and discriminator over time, plot them, and interpret them.

On MINIST data,

The optimizers used are:

```
d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002)
g_optimizer = optim.Adam(generator.parameters(), lr=0.0002)
```

loss function:

```
loss = nn.BCELoss()
```

On CIFAR data,

The optimizers used are:

```
    d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
    g_optimizer = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))
```

loss function:

```
loss = nn.BCELoss()
```

In [ ]:

```
import os
import numpy as np
import errno
import torchvision.utils as vutils
from tensorboardX import SummaryWriter
from IPython import display
from matplotlib import pyplot as plt
import torch

'''
    TensorBoard Data will be stored in './runs' path
'''

class Logger:

    def __init__(self, model_name, data_name):
        self.model_name = model_name
        self.data_name = data_name

        self.comment = '{}_{}'.format(model_name, data_name)
        self.data_subdir = '{}/{}'.format(model_name, data_name)

        # TensorBoard
        self.writer = SummaryWriter(comment=self.comment)

    def log(self, d_error, g_error, epoch, n_batch, num_batches):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()

        step = Logger._step(epoch, n_batch, num_batches)
        self.writer.add_scalar(
            '{}/D_error'.format(self.comment), d_error, step)
        self.writer.add_scalar(
            '{}/G_error'.format(self.comment), g_error, step)

    def log_images(self, images, num_images, epoch, n_batch, num_batches, format='NCH
W', normalize=True):
        '''
        input images are expected in format (NCHW)
        '''
        if type(images) == np.ndarray:
            images = torch.from_numpy(images)

        if format=='NHWC':
            images = images.transpose(1,3)


        step = Logger._step(epoch, n_batch, num_batches)
        img_name = '{}/images{}'.format(self.comment, '')

        # Make horizontal grid from image tensor
        horizontal_grid = vutils.make_grid(
            images, normalize=normalize, scale_each=True)
        # Make vertical grid from image tensor
        nrows = int(np.sqrt(num_images))
```

```
        grid = vutils.make_grid(
            images, nrow=nrows, normalize=True, scale_each=True)

        # Add horizontal images to tensorboard
        self.writer.add_image(img_name, horizontal_grid, step)

        # Save plots
        self.save_torch_images(horizontal_grid, grid, epoch, n_batch)

    def save_torch_images(self, horizontal_grid, grid, epoch, n_batch, plot_horizontal=
True):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)

        # Plot and save horizontal
        fig = plt.figure(figsize=(16, 16))
        plt.imshow(np.moveaxis(horizontal_grid.numpy(), 0, -1))
        plt.axis('off')
        if plot_horizontal:
            display.display(plt.gcf())
        self._save_images(fig, epoch, n_batch, 'hori')
        plt.close()

        # Save squared
        fig = plt.figure()
        plt.imshow(np.moveaxis(grid.numpy(), 0, -1))
        plt.axis('off')
        self._save_images(fig, epoch, n_batch)
        plt.close()

    def _save_images(self, fig, epoch, n_batch, comment=''):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        fig.savefig('{}/{}_epoch_{}_batch_{}.png'.format(out_dir,
                                                         comment, epoch, n_batch))

    def display_status(self, epoch, num_epochs, n_batch, num_batches, d_error, g_error,
d_pred_real, d_pred_fake):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()
        if isinstance(d_pred_real, torch.autograd.Variable):
            d_pred_real = d_pred_real.data
        if isinstance(d_pred_fake, torch.autograd.Variable):
            d_pred_fake = d_pred_fake.data


        print('Epoch: [{}/{}], Batch Num: [{}/{}]'.format(
            epoch,num_epochs, n_batch, num_batches)
             )
        print('Discriminator Loss: {:.4f}, Generator Loss: {:.4f}'.format(d_error, g_er
ror))
        print('D(x): {:.4f}, D(G(z)): {:.4f}'.format(d_pred_real.mean(), d_pred_fake.me
an()))

    def save_models(self, generator, discriminator, epoch):
```

```
        out_dir = './data/models/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        torch.save(generator.state_dict(),
                   '{}/G_epoch_{}'.format(out_dir, epoch))
        torch.save(discriminator.state_dict(),
                   '{}/D_epoch_{}'.format(out_dir, epoch))

    def close(self):
        self.writer.close()

    # Private Functionality

    @staticmethod
    def _step(epoch, n_batch, num_batches):
        return epoch * num_batches + n_batch

    @staticmethod
    def _make_dir(directory):
        try:
            os.makedirs(directory)
        except OSError as e:
            if e.errno != errno.EEXIST:
                raise
```

```
/usr/local/lib/python3.8/dist-packages/tqdm/auto.py:22: TqdmWarning: IProg
ress not found. Please update jupyter and ipywidgets. See https://ipywidge
ts.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
/usr/local/lib/python3.8/dist-packages/torchvision/io/image.py:11: UserWar
ning: Failed to load image Python extension: /usr/local/lib/python3.8/dist
-packages/torchvision/image.so: undefined symbol: _ZNK3c1010TensorImpl36is
_contiguous_nondefault_policy_implENS_12MemoryFormatE
  warn(f"Failed to load image Python extension: {e}")
```

1.1 Vanilla GAN for MNIST dataset

Next we'll download the MNIST dataset as a small dataset we can get things running on quickly:

1.1.1 Load MNIST dataset

In [ ]:

```
import torch
from torch import nn, optim
from torchvision import transforms, datasets

DATA_FOLDER = './torch_data/VGAN/MNIST'
def mnist_data():
    compose = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize([0.5], [0.5])
        ])
    out_dir = '{}/dataset'.format(DATA_FOLDER)
    return datasets.MNIST(root=out_dir, train=True, transform=compose, download=True)

# Load Dataset and attach a DataLoader

data = mnist_data()
batch_size = 100
data_loader = torch.utils.data.DataLoader(data, batch_size=batch_size, shuffle=True)
num_batches = len(data_loader)
num_batches
```

```
600
```

1.1.2 Generator

The generator in a GAN is the model you want to help achieve high performance. A generator generates different objects because of the random noise sample. If we make small changes to the noise, we should be able to see corresponding small changes to the output. The generator is driven by a noise vector sampled from a latent space (the domain of p_z) and transforms that noise sample into an element of the domain of p_{data}.

In [ ]:

```
class GeneratorNet(torch.nn.Module):
    """
    A three hidden-layer generative neural network
    """
    def __init__(self):
        super(GeneratorNet, self).__init__()
        n_features = 100
        n_out = 784

        self.hidden0 = nn.Sequential(
            nn.Linear(n_features, 256),
            nn.LeakyReLU(0.2)
        )
        self.hidden1 = nn.Sequential(
            nn.Linear(256, 512),
            nn.LeakyReLU(0.2)
        )
        self.hidden2 = nn.Sequential(
            nn.Linear(512, 1024),
            nn.LeakyReLU(0.2)
        )

        self.out = nn.Sequential(
            nn.Linear(1024, n_out),
            nn.Tanh()
        )

    def forward(self, x):
        x = self.hidden0(x)
        x = self.hidden1(x)
        x = self.hidden2(x)
        x = self.out(x)
        return x

# Function to create noise samples for the generator's input

def noise(size):
    n = torch.randn(size, 100)
    if torch.cuda.is_available(): return n.cuda()
    return n
```

1.3 Discriminator

The discriminator is a type of classifier, but it is just to classify its input as real or fake. When a fake sample from the generator is given, it should ouptut 0 for fake:

In [ ]:

```
class DiscriminatorNet(torch.nn.Module):
    """
    A three hidden-layer discriminative neural network
    """
    def __init__(self):
        super(DiscriminatorNet, self).__init__()
        n_features = 784
        n_out = 1

        self.hidden0 = nn.Sequential(
            nn.Linear(n_features, 1024),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )
        self.hidden1 = nn.Sequential(
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )
        self.hidden2 = nn.Sequential(
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )
        self.out = nn.Sequential(
            torch.nn.Linear(256, n_out),
            torch.nn.Sigmoid()
        )

    def forward(self, x):
        x = self.hidden0(x)
        x = self.hidden1(x)
        x = self.hidden2(x)
        x = self.out(x)
        return x

def images_to_vectors(images):
    return images.view(images.size(0), 784)

def vectors_to_images(vectors):
    return vectors.view(vectors.size(0), 1, 28, 28)
```

1.1.4 Create the modules

Let's create an instance of the generator and discriminator:

In [ ]:

```
discriminator = DiscriminatorNet()
generator = GeneratorNet()

if torch.cuda.is_available():
    discriminator.cuda()
    generator.cuda()
```

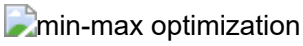
1.1.5 Set up the optimizers

The optimization is a min-max game. The generator wants to minimize the objective function, whereas the discriminator wants to maximize the same objective function. The discriminator's loss function is binary cross entropy:
$$\mathcal{L}_D = \max_D\mathcal{L}(D;G)=\mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_x{z}}[\log (1-D(G(z))]$$

The generator does't affect the first term of $\mathcal{L}_D$, so its goal is a bit simpler, to minimize the second term of $\mathcal{L}_D$:
$$\mathcal{L}_G = \min_G\mathcal{L}(G;D)=\mathbb{E}_{z \sim p_x{z}}[\log (D(G(z))]$$

Putting these together we have
$$\min_G\max_D\mathcal{L}(D;G)=\mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_x{z}}[\log (1-D(G(z))]$$

Here is a diagram of the objective function:



In [ ]:

```
# Optimizers

d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002)
g_optimizer = optim.Adam(generator.parameters(), lr=0.0002)

# Loss function

loss = nn.BCELoss()

# How many epochs to train for

num_epochs = 200

# Number of steps to apply to the discriminator for each step of the generator (1 in Go
odfellow et al.)

d_steps = 1
```

1.1.6 Training

The targets for the discriminator may be 0 or 1 depending on whether we're giving it real or fake data:

In [ ]:

```
def real_data_target(size):
    '''
    Tensor containing ones, with shape = size
    '''
    data = torch.ones(size, 1)
    if torch.cuda.is_available(): return data.cuda()
    return data

def fake_data_target(size):
    '''
    Tensor containing zeros, with shape = size
    '''
    data = torch.zeros(size, 1)
    if torch.cuda.is_available(): return data.cuda()
    return data
```

In [ ]:

```
def train_discriminator(optimizer, real_data, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate real data
    prediction_real = discriminator(real_data)
    error_real = loss(prediction_real, real_data_target(real_data.size(0)))
    error_real.backward()

    # Propagate fake data
    prediction_fake = discriminator(fake_data)
    error_fake = loss(prediction_fake, fake_data_target(real_data.size(0)))
    error_fake.backward()

    # Take a step
    optimizer.step()

    # Return error
    return error_real + error_fake, prediction_real, prediction_fake
```

In [ ]:

```
def train_generator(optimizer, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate the fake data through the discriminator and backpropagate.
    # Note that since we want the generator to output something that gets
    # the discriminator to output a 1, we use the real data target here.
    prediction = discriminator(fake_data)
    error = loss(prediction, real_data_target(prediction.size(0)))
    error.backward()

    # Update weights with gradients
    optimizer.step()

    # Return error
    return error
```

1.1.7 Generate test noise samples

Let's generate some noise vectors to use as inputs to the generator. We'll use these samples repeatedly to see the evolution of the generator over time.

In [ ]:

```
num_test_samples = 16
test_noise = noise(num_test_samples)
test_noise
```

```
tensor([[ 1.0669,  0.7644, -0.5407,  ...,  0.2738,  1.6525,  1.0689],
        [ 0.1528,  0.9268,  0.7195,  ...,  1.1006,  0.8663,  0.5206],
        [ 0.4634, -0.4977,  0.0568,  ..., -0.1486,  0.1316, -1.8938],
        ...,
        [-0.6337,  0.5107, -1.0438,  ..., -0.7131, -0.9282, -1.3350],
        [-1.4199, -1.0639,  2.1478,  ..., -0.0728, -0.3057,  0.4891],
        [-0.4763,  0.0691, -0.4890,  ...,  0.5116,  1.1332,  0.5095]],
       device='cuda:0')
```

1.1.8 Start training

Now let's train the model:

In [ ]:

```
logger = Logger(model_name='VGAN', data_name='MNIST')

for epoch in range(num_epochs):
    for n_batch, (real_batch,_) in enumerate(data_loader):

        # Train discriminator on a real batch and a fake batch

        real_data = images_to_vectors(real_batch)
        if torch.cuda.is_available(): real_data = real_data.cuda()
        fake_data = generator(noise(real_data.size(0))).detach()
        d_error, d_pred_real, d_pred_fake = train_discriminator(d_optimizer,
                                                                real_data, fake_data)

        # Train generator

        fake_data = generator(noise(real_batch.size(0)))
        g_error = train_generator(g_optimizer, fake_data)

        # Log errors and display progress

        logger.log(d_error, g_error, epoch, n_batch, num_batches)
        if (n_batch) % 100 == 0:
            display.clear_output(True)
            # Display Images
            test_images = vectors_to_images(generator(test_noise)).data.cpu()
            logger.log_images(test_images, num_test_samples, epoch, n_batch, num_batche
s);
            # Display status Logs
            logger.display_status(
                epoch, num_epochs, n_batch, num_batches,
                d_error, g_error, d_pred_real, d_pred_fake
            )

        # Save model checkpoints
        logger.save_models(generator, discriminator, epoch)
```

```
Epoch: [199/200], Batch Num: [500/600]
Discriminator Loss: 1.3389, Generator Loss: 0.8982
D(x): 0.5126, D(G(z)): 0.4360
```

1.1.9 Plot

In [ ]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('tensorboard_plot/VGAN_MNIST.jpg')
plt.figure(figsize=(20,5))
plt.imshow(img)
```

1.2 DCGAN for CIFAR

The DCGAN is a GAN with a generator designed to do just that, generate larger RGB images using convolutional layers.

1.2.1 Load CIFAR dataset

In [ ]:

```
import torch
from torch import nn, optim
from torchvision import transforms, datasets

DATA_FOLDER = './torch_data/DCGAN/CIFAR'
def cifar_data():
    compose = transforms.Compose(
        [transforms.Resize(64),
            transforms.ToTensor(),
            transforms.Normalize((.5, .5, .5), (.5, .5, .5))
        ])
    out_dir = '{}/dataset'.format(DATA_FOLDER)
    return datasets.CIFAR10(root=out_dir, train=True, transform=compose, download=True)

# Load Dataset and attach a DataLoader

data = cifar_data()
batch_size = 100
data_loader = torch.utils.data.DataLoader(data, batch_size=batch_size, shuffle=True)
num_batches = len(data_loader)
num_batches
```

```
Files already downloaded and verified
```

```
500
```

1.2.2 Discriminator

Here are PyTorch Modules for them:

In [ ]:

```
#NO BIASES BECAUSE BATCHNORM!!!
class DiscriminativeNet(torch.nn.Module):

    def __init__(self):
        super(DiscriminativeNet, self).__init__()

        self.conv1 = nn.Sequential(
            nn.Conv2d(
                in_channels=3, out_channels=128, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(
                in_channels=128, out_channels=256, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv3 = nn.Sequential(
            nn.Conv2d(
                in_channels=256, out_channels=512, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv4 = nn.Sequential(
            nn.Conv2d(
                in_channels=512, out_channels=1024, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(1024),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.out = nn.Sequential(
            nn.Linear(1024*4*4, 1), # #filters,height,width
            nn.Sigmoid(),
        )

    def forward(self, x):
        # Convolutional layers
        x = self.conv1(x)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.conv4(x)
        # Flatten and apply sigmoid
        x = x.view(-1, 1024*4*4)
        x = self.out(x)
        return x
```

1.2.3 Generator

The generator is using transpose convolutions with batch normalization:

In [ ]:

```
class GenerativeNet(torch.nn.Module):

    def __init__(self):
        super(GenerativeNet, self).__init__()

        self.linear = torch.nn.Linear(100, 1024*4*4)

        self.conv1 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=1024, out_channels=512, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True)
        )
        self.conv2 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=512, out_channels=256, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True)
        )
        self.conv3 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=256, out_channels=128, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True)
        )
        self.conv4 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=128, out_channels=3, kernel_size=4,
                stride=2, padding=1, bias=False
            )
        )
        self.out = torch.nn.Tanh()
    '''
    "The ReLU activation (Nair & Hinton, 2010) is used in the generator
    with the exception of the output layer which uses the Tanh function.
    We observed that using a bounded activation allowed the model to learn
    more quickly to saturate and cover the color space of the training distribution.
    Within the discriminator we found the leaky rectified activation
    (Maas et al., 2013) (Xu et al., 2015)to work well, especially for higher resolution
modeling.
    This is in contrast to the original GAN paper,
    which used the maxout activation (Goodfellow et al., 2013)."
    '''
    def forward(self, x):
        # Project and reshape
        x = self.linear(x)
        x = x.view(x.shape[0], 1024, 4, 4)
        # Convolutional layers
        x = self.conv1(x)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.conv4(x)
        # Apply Tanh
```

```
        return self.out(x)

# Function to create noise samples for the generator's input

def noise(size):
    n = torch.randn(size, 100)
    if torch.cuda.is_available(): return n.cuda()
    return n
```

1.2.4 Initialize weights

Let's create a generator and discriminator and initialize their weights:

In [ ]:

```
# Custom weight initialization

def init_weights(m):
    classname = m.__class__.__name__
    if classname.find('Conv') != -1 or classname.find('BatchNorm') != -1:
        m.weight.data.normal_(0.00, 0.02)

# Instantiate networks

generator = GenerativeNet()
generator.apply(init_weights)
discriminator = DiscriminativeNet()
discriminator.apply(init_weights)

# Enable cuda if available

if torch.cuda.is_available():
    generator.cuda()
    discriminator.cuda()
```

1.2.5 Optimizers

Next, we set up the optimizers and loss function.

In [ ]:

```
# Optimizers

d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
g_optimizer = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))

# Loss function
loss = nn.BCELoss()

# Number of epochs of training
num_epochs = 30
```

1.2.6 Training

As before, we'll generate a fixed set of noise samples to see the evolution of the generator over time then start training:

In [ ]:

```
def real_data_target(size):
    '''
    Tensor containing ones, with shape = size
    '''
    data = torch.ones(size, 1)
    if torch.cuda.is_available(): return data.cuda()
    return data

def fake_data_target(size):
    '''
    Tensor containing zeros, with shape = size
    '''
    data = torch.zeros(size, 1)
    if torch.cuda.is_available(): return data.cuda()
    return data
```

In [ ]:

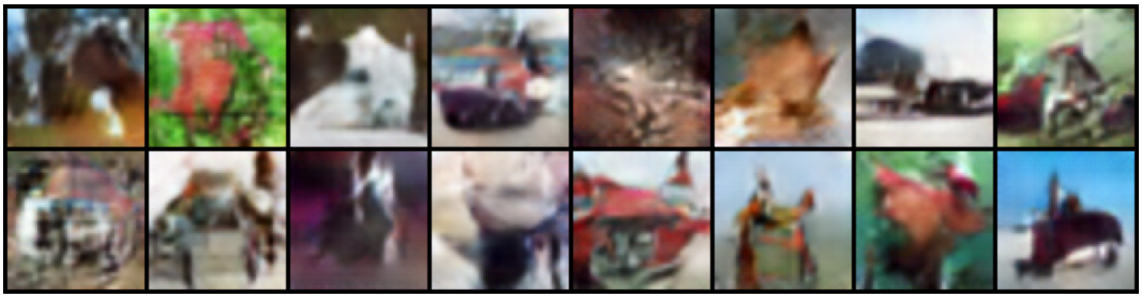
```
def train_discriminator(optimizer, real_data, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate real data
    prediction_real = discriminator(real_data)
    error_real = loss(prediction_real, real_data_target(real_data.size(0)))
    error_real.backward()

    # Propagate fake data
    prediction_fake = discriminator(fake_data)
    error_fake = loss(prediction_fake, fake_data_target(real_data.size(0)))
    error_fake.backward()

    # Take a step
    optimizer.step()

    # Return error
    return error_real + error_fake, prediction_real, prediction_fake
```

In [ ]:

```
def train_generator(optimizer, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate the fake data through the discriminator and backpropagate.
    # Note that since we want the generator to output something that gets
    # the discriminator to output a 1, we use the real data target here.
    prediction = discriminator(fake_data)
    error = loss(prediction, real_data_target(prediction.size(0)))
    error.backward()

    # Update weights with gradients
    optimizer.step()

    # Return error
    return error
```

In [ ]:

```
num_test_samples = 16
test_noise = noise(num_test_samples)

logger = Logger(model_name='DCGAN', data_name='CIFAR10')

for epoch in range(num_epochs):
    for n_batch, (real_data,_) in enumerate(data_loader):

        # Train Discriminator

        #if torch.cuda.is_available(): real_data = real_data.cuda(device)
        if torch.cuda.is_available(): real_data = real_data.cuda()
        fake_data = generator(noise(real_data.size(0))).detach()
        d_error, d_pred_real, d_pred_fake = train_discriminator(d_optimizer,
                                                                real_data, fake_data)

        # Train Generator

        fake_data = generator(noise(real_data.size(0)))
        g_error = train_generator(g_optimizer, fake_data)

        # Log error and display progress
        logger.log(d_error, g_error, epoch, n_batch, num_batches)
        if (n_batch) % 100 == 0:
            display.clear_output(True)
            # Display Images
            test_images = generator(test_noise).data.cpu()
            logger.log_images(test_images, num_test_samples, epoch, n_batch, num_batche
s);
            # Display status Logs
            logger.display_status(
                epoch, num_epochs, n_batch, num_batches,
                d_error, g_error, d_pred_real, d_pred_fake
            )

        # Save model checkpoints
        logger.save_models(generator, discriminator, epoch)
```



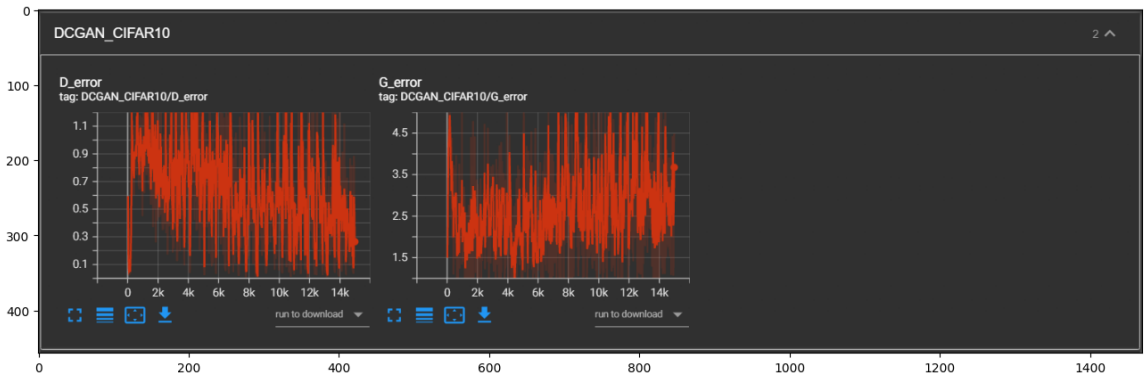
```
Epoch: [29/30], Batch Num: [400/500]
Discriminator Loss: 0.1189, Generator Loss: 3.5956
D(x): 0.9392, D(G(z)): 0.0515
```

1.2.7 Plot

In [ ]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('tensorboard_plot/DCGAN_FICAR10.png')
plt.figure(figsize=(20,5))
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7f71083c7460>
```



Evaluation on MINIST

The training of MNIST dataset on VGAN produces a positive results at 200th epoch. As shown in the plots, it can be seen that both losses start to converge. Moreover, D(x) also starts to get closer to 0.5, this indicates that the performance of the discriminator is also at its optimal.

Evaluation on CIFAR

Simuilar to the training of MNIST dataset, the training CIFAR also shows somewhat positive results. D(x) also starts to get closer to 0.5 and the losses start to converge. One thing to notice is that the losses of MNIST are less fluctuating than those of CIFAR.

Task 2.

Develop your own GAN to model data generated as follows:
$$\begin{eqnarray} \theta & \sim & {\cal U}(0,2\pi) \\ r & \sim & {\cal N}(0, 1) \\ \mathbf{x} & \leftarrow & \begin{cases} \begin{bmatrix} (10+r)\cos\theta \\ (10+r)\sin\theta + 10\end{bmatrix} & \frac{1}{2}\pi \le \theta \le \frac{3}{2}\pi \\ \begin{bmatrix} (10+r)\cos\theta \\ (10+r)\sin\theta - 10\end{bmatrix} & \mathrm{otherwise} \end{cases} \end{eqnarray} $$

You should create a PyTorch DataSet that generates the 2D data in the `__init__()` method, outputs a sample in the `__getitem__()` method, and returns the dataset size in the `__len__()` method.

Use the vanilla GAN approach above with an appropriate structure for the generator.

Can your GAN generate a convincing facsimile of a set of samples from the actual distribution?

On SNAKE data,

The optimizers used are:

```
    d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5,
0.999))<br>
    g_optimizer = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.99
9))
```

loss function:

```
    loss = nn.BCELoss()
```

NOTE: Tanh() activation function in Generator is removed due to the data range of SNAKE dataset.

Tanh limits the range to be in between [-1,1] which is not suitable for the dataset of SNAKE.

In [ ]:

```
import os
import numpy as np
import errno
import torchvision.utils as vutils
from tensorboardX import SummaryWriter
from IPython import display
from matplotlib import pyplot as plt
import torch

'''
    TensorBoard Data will be stored in './runs' path
'''

class Logger:

    def __init__(self, model_name, data_name):
        self.model_name = model_name
        self.data_name = data_name

        self.comment = '{}_{}'.format(model_name, data_name)
        self.data_subdir = '{}/{}'.format(model_name, data_name)

        # TensorBoard
        self.writer = SummaryWriter(comment=self.comment)

    def log(self, d_error, g_error, epoch, n_batch, num_batches):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()

        step = Logger._step(epoch, n_batch, num_batches)
        self.writer.add_scalar(
            '{}/D_error'.format(self.comment), d_error, step)
        self.writer.add_scalar(
            '{}/G_error'.format(self.comment), g_error, step)

    def log_images(self, images, num_images, epoch, n_batch, num_batches, format='NCH
W', normalize=True):
        '''
        input images are expected in format (NCHW)
        '''
        if type(images) == np.ndarray:
            images = torch.from_numpy(images)

        if format=='NHWC':
            images = images.transpose(1,3)


        step = Logger._step(epoch, n_batch, num_batches)
        img_name = '{}/images{}'.format(self.comment, '')

        # Make horizontal grid from image tensor
        horizontal_grid = vutils.make_grid(
            images, normalize=normalize, scale_each=True)
        # Make vertical grid from image tensor
        nrows = int(np.sqrt(num_images))
```

```
        grid = vutils.make_grid(
            images, nrow=nrows, normalize=True, scale_each=True)

        # Add horizontal images to tensorboard
        self.writer.add_image(img_name, horizontal_grid, step)

        # Save plots
        self.save_torch_images(horizontal_grid, grid, epoch, n_batch)

    def save_torch_images(self, horizontal_grid, grid, epoch, n_batch, plot_horizontal=
True):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)

        # Plot and save horizontal
        fig = plt.figure(figsize=(16, 16))
        plt.imshow(np.moveaxis(horizontal_grid.numpy(), 0, -1))
        plt.axis('off')
        if plot_horizontal:
            display.display(plt.gcf()) #get current axis
        self._save_images(fig, epoch, n_batch, 'hori')
        plt.close()

        # Save squared
        fig = plt.figure()
        plt.imshow(np.moveaxis(grid.numpy(), 0, -1))
        plt.axis('off')
        self._save_images(fig, epoch, n_batch)
        plt.close()

    def _save_images(self, fig, epoch, n_batch, comment=''):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        fig.savefig('{}/{}_epoch_{}_batch_{}.png'.format(out_dir,
                                                         comment, epoch, n_batch))

    def display_status(self, epoch, num_epochs, n_batch, num_batches, d_error, g_error,
d_pred_real, d_pred_fake):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()
        if isinstance(d_pred_real, torch.autograd.Variable):
            d_pred_real = d_pred_real.data
        if isinstance(d_pred_fake, torch.autograd.Variable):
            d_pred_fake = d_pred_fake.data


        print('Epoch: [{}/{}], Batch Num: [{}/{}]'.format(
            epoch,num_epochs, n_batch, num_batches)
             )
        print('Discriminator Loss: {:.4f}, Generator Loss: {:.4f}'.format(d_error, g_er
ror))
        print('D(x): {:.4f}, D(G(z)): {:.4f}'.format(d_pred_real.mean(), d_pred_fake.me
an()))

    def save_models(self, generator, discriminator, epoch):
```

```
        out_dir = './data/models/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        torch.save(generator.state_dict(),
                   '{}/G_epoch_{}'.format(out_dir, epoch))
        torch.save(discriminator.state_dict(),
                   '{}/D_epoch_{}'.format(out_dir, epoch))

    def close(self):
        self.writer.close()

    # Private Functionality

    @staticmethod
    def _step(epoch, n_batch, num_batches):
        return epoch * num_batches + n_batch

    @staticmethod
    def _make_dir(directory):
        try:
            os.makedirs(directory)
        except OSError as e:
            if e.errno != errno.EEXIST:
                raise
```

```
/usr/local/lib/python3.8/dist-packages/tqdm/auto.py:22: TqdmWarning: IProg
ress not found. Please update jupyter and ipywidgets. See https://ipywidge
ts.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
/usr/local/lib/python3.8/dist-packages/torchvision/io/image.py:11: UserWar
ning: Failed to load image Python extension: /usr/local/lib/python3.8/dist
-packages/torchvision/image.so: undefined symbol: _ZNK3c1010TensorImpl36is
_contiguous_nondefault_policy_implENS_12MemoryFormatE
  warn(f"Failed to load image Python extension: {e}")
```

Vanilla GAN for SNAKE dataset

Next we'll download the MNIST dataset as a small dataset we can get things running on quickly:

3.1 SNAKE dataset class

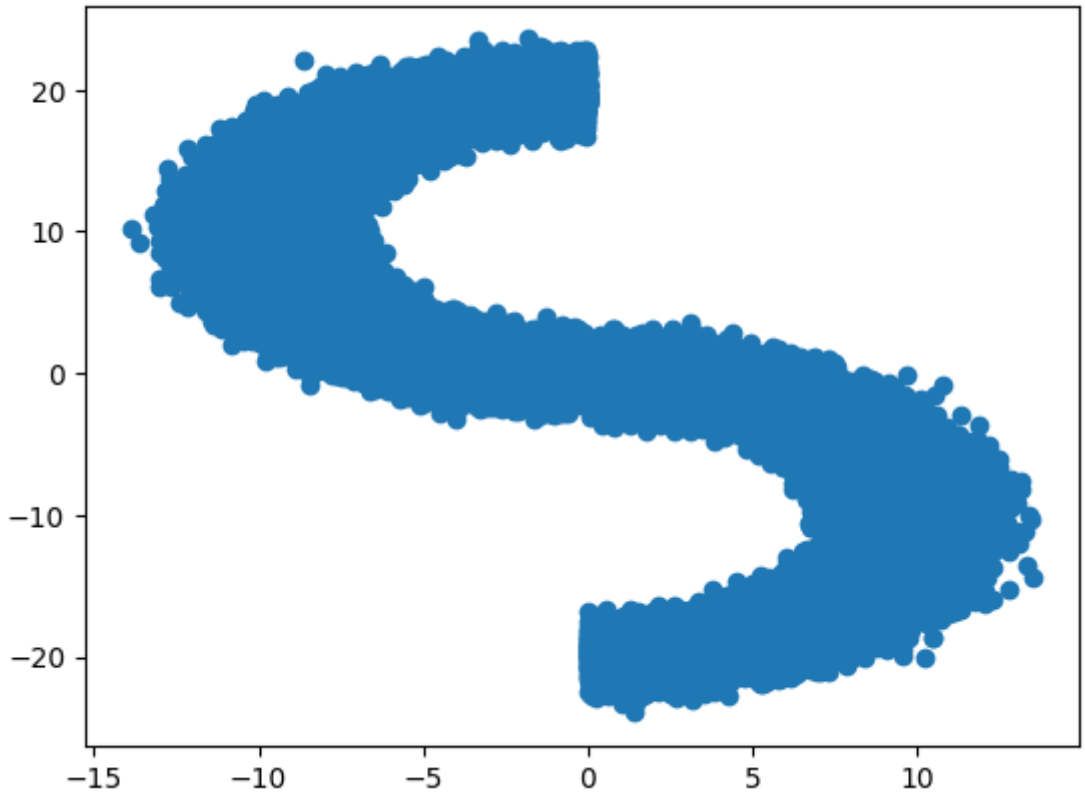
In [ ]:

```
import numpy as np
import torch
class snake_dataset():

    def __init__(self, num_sample = 1000):
        self.pi = np.pi
        self.num_sample = num_sample
        self.r = torch.randn(self.num_sample,1)
        self.theta = torch.FloatTensor(self.num_sample,1).uniform_(0,2*self.pi)
        self.a = 10 + self.r
        self.data = torch.empty(self.num_sample,2)
        #self.label = 0
        # self.Y = torch.empty(self.num_sample,1)
        for i in range(self.num_sample):
            if  0.5* self.pi <= self.theta[i] and self.theta[i] <= (3/2) * self.pi :
                self.a = 10 + self.r[i]
                self.x_data = self.a * torch.cos(self.theta[i])
                self.y_data = (self.a * torch.sin(self.theta[i])) + 10
                self.data[i,0] = self.x_data
                self.data[i,1] = self.y_data

            else:
                self.a = 10 + self.r[i]
                self.x_data = self.a * torch.cos(self.theta[i])
                self.y_data = (self.a * torch.sin(self.theta[i])) - 10
                self.data[i,0] = self.x_data
                self.data[i,1] = self.y_data

        self.len = self.data.shape[0]

    def __getitem__(self, index):
        # return (self.X[index], self.Y[index])
        return self.data[index]

    def __len__(self):
        return self.len
```

3.2 Generate snake dataset

In [ ]:

```
import torch
from torch import nn, optim
from torchvision import transforms, datasets

# Load Dataset and attach a DataLoader

from dataset_snake import snake_dataset
import matplotlib.pyplot as plt
num_sample = 100000
dataset = snake_dataset(num_sample)
plt.scatter(dataset.data[:,0],dataset.data[:,1])

batch_size=100
data_loader = torch.utils.data.DataLoader(dataset, batch_size=batch_size, shuffle=True)
num_batches = len(data_loader)
```



3.3 Generator

This "vanilla" GAN is the simplest GAN network architecture.

In [ ]:

```
class GeneratorNet(torch.nn.Module):
    """
    A three hidden-layer generative neural network
    """
    def __init__(self):
        super(GeneratorNet, self).__init__()
        n_features = 2
        n_out = 2

        self.hidden0 = nn.Sequential(
            nn.Linear(n_features, 256),
            nn.LeakyReLU(0.2)
        )
        self.hidden1 = nn.Sequential(
            nn.Linear(256, 256),
            nn.LeakyReLU(0.2)
        )
        self.out = nn.Sequential(
            nn.Linear(256, n_out),
            #nn.Tanh() #Tanh because output image = [0,1]
        )

    def forward(self, x):
        #print("generator")
        x = self.hidden0(x)
        x = self.hidden1(x)
        x = self.out(x)
        return x
```

3.4 Discriminator

The discriminator has the responsibity to classify its input as real or fake. When a fake sample from the generator is given, it should ouptut 0 for fake:

In [ ]:

```
class DiscriminatorNet(torch.nn.Module):
    """
    A three hidden-layer discriminative neural network
    """
    def __init__(self):
        super(DiscriminatorNet, self).__init__()
        n_features = 2
        n_out = 1

        self.hidden0 = nn.Sequential(
            nn.Linear(n_features, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )
        self.hidden1 = nn.Sequential(
            nn.Linear(256, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.out = nn.Sequential(
            torch.nn.Linear(256, n_out),
            torch.nn.Sigmoid()
        )

    def forward(self, x):
        #print("discriminator")
        x = self.hidden0(x)
        x = self.hidden1(x)
        x = self.out(x)
        return x

# def images_to_vectors(images):
#     return images.view(images.size(0), 784)

# def vectors_to_images(vectors):
#     return vectors.view(vectors.size(0), 1, 28, 28)
```

3.5 Create the modules

Let's create an instance of the generator and discriminator:

In [ ]:

```
discriminator = DiscriminatorNet()
generator = GeneratorNet()

device = torch.device('cuda:2') if torch.cuda.is_available() else torch.device("cpu")
print("Configured device: ", device)
#device = 1
if torch.cuda.is_available():
    discriminator.cuda(device)
    generator.cuda(device)
```

```
Configured device:  cuda:2
```

3.6 Set up the optimizers and loss function

In [ ]:

```
# Optimizers

d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
g_optimizer = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))

# Loss function

loss = nn.BCELoss()

# How many epochs to train for

num_epochs = 30

# Number of steps to apply to the discriminator for each step of the generator (1 in Go
odfellow et al.)

d_steps = 1
```

3.7 Training

The targets for the discriminator may be 0 or 1 depending on whether we're giving it real or fake data:

In [ ]:

```
def real_data_target(size):
    '''
    Tensor containing ones, with shape = size
    '''
    data = torch.ones(size, 1)
    if torch.cuda.is_available(): return data.cuda(device)
    return data

def fake_data_target(size):
    '''
    Tensor containing zeros, with shape = size
    '''
    data = torch.zeros(size, 1)
    if torch.cuda.is_available(): return data.cuda(device)
    return data
```

Here's a function for a single step for the discriminator:

In [ ]:

```
def train_discriminator(optimizer, real_data, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate real data
    prediction_real = discriminator(real_data)
    error_real = loss(prediction_real, real_data_target(real_data.size(0)))
    error_real.backward()

    # Propagate fake data
    prediction_fake = discriminator(fake_data)
    error_fake = loss(prediction_fake, fake_data_target(real_data.size(0)))
    error_fake.backward()

    # Take a step
    optimizer.step()

    # Return error
    return error_real + error_fake, prediction_real, prediction_fake
```

And here's a function for a single step of the generator:

In [ ]:

```
def train_generator(optimizer, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate the fake data through the discriminator and backpropagate.
    # Note that since we want the generator to output something that gets
    # the discriminator to output a 1, we use the real data target here.
    prediction = discriminator(fake_data)
    error = loss(prediction, real_data_target(prediction.size(0)))
    error.backward()

    # Update weights with gradients
    optimizer.step()

    # Return error
    return error
```

3.8 Generate test noise samples

Let's generate some noise vectors to use as inputs to the generator. We'll use these samples repeatedly to see the evolution of the generator over time.

In [ ]:

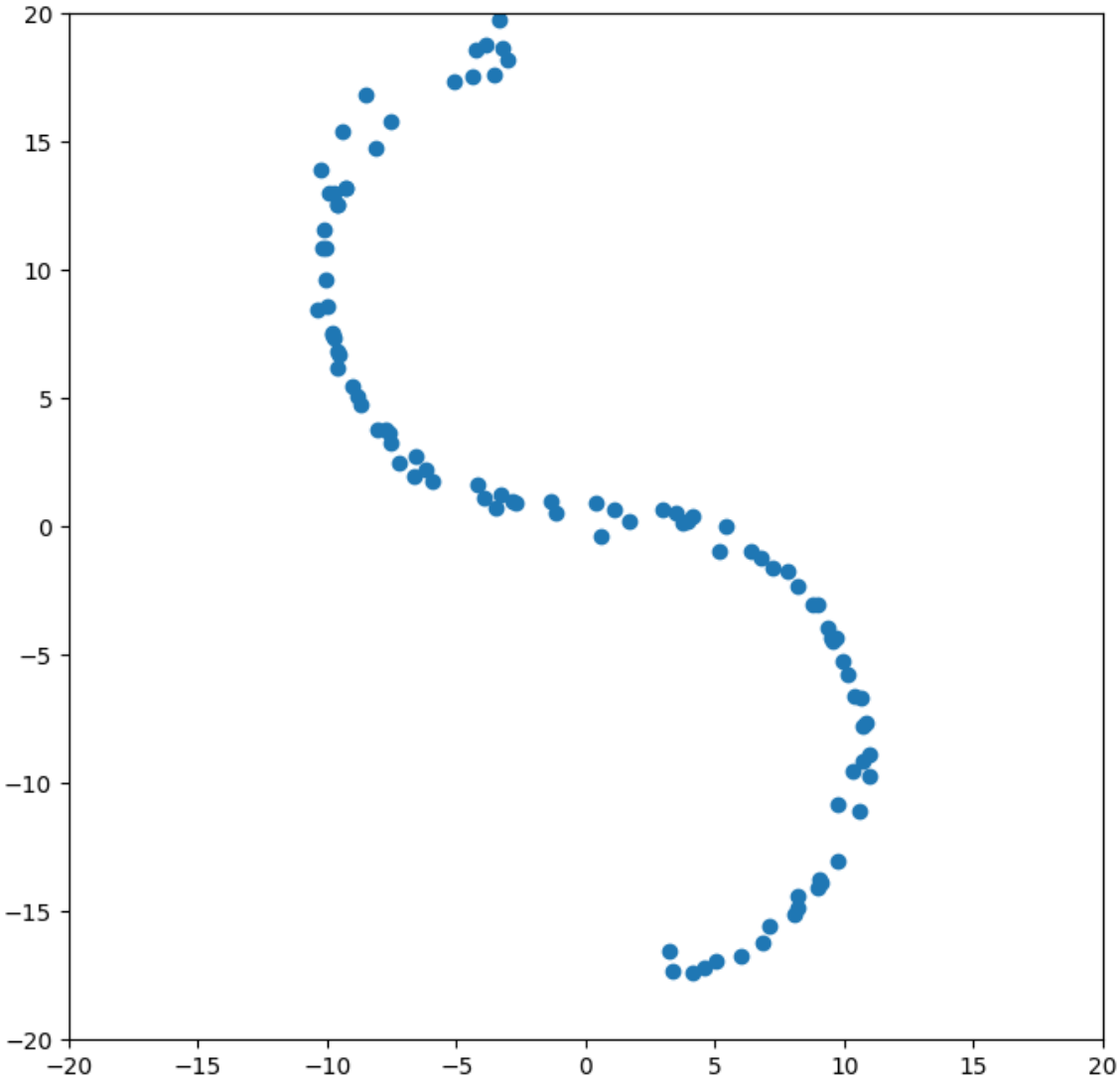
```
# Function to create noise samples for the generator's input

def noise(size):
    n = torch.randn(size, 2) #[size vector of length 100]
    if torch.cuda.is_available(): return n.cuda(device)
    return n

num_test_samples = 100
test_noise = noise(num_test_samples)
```

3.9 Start training

Now let's train the model:

In [ ]:

```
def plt_output(fake_data):
    plt.figure(figsize=(8,8))
    plt.xlim(-20,20)
    plt.ylim(-20,20)
    plt.scatter(fake_data[:,0], fake_data[:,1])
    plt.show()

logger = Logger(model_name='VGAN', data_name='SNAKE')

for epoch in range(num_epochs):
    for n_batch, real_batch in enumerate(data_loader):
        # Train discriminator on a real batch and a fake batch

        #real_data = images_to_vectors(real_batch)
        real_data = real_batch
        real_data = real_data.cuda(device)
        #if torch.cuda.is_available(): real_data = real_data.cuda(device)
        fake_data = generator(noise(real_data.size(0))).detach()
        d_error, d_pred_real, d_pred_fake = train_discriminator(d_optimizer,
                                                                real_data, fake_data)

        # Train generator

        fake_data = generator(noise(real_batch.size(0)))
        g_error = train_generator(g_optimizer, fake_data)

        # Log errors and display progress

        logger.log(d_error, g_error, epoch, n_batch, num_batches)
        if (n_batch) % 10 == 0:
            display.clear_output(True)
            # Display Images
            #test_images = vectors_to_images(generator(test_noise)).data.cpu()
            #test_images = generator(test_noise).data.cpu()
            # print(test_images.shape)
            test_plot = plt_output(generator(test_noise).cpu().detach().numpy())
            #logger.log_images(test_images, num_test_samples, epoch, n_batch, num_batch
es);
            # Display status Logs
            logger.display_status(
                epoch, num_epochs, n_batch, num_batches,
                d_error, g_error, d_pred_real, d_pred_fake
            )

        # Save model checkpoints
        logger.save_models(generator, discriminator, epoch)
```

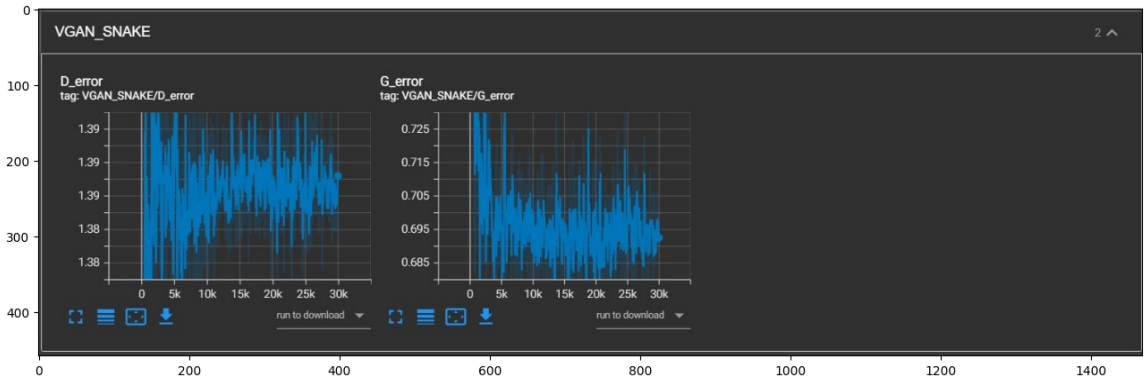



```
Epoch: [29/30], Batch Num: [990/1000]
Discriminator Loss: 1.3851, Generator Loss: 0.6985
D(x): 0.4976, D(G(z)): 0.4969
```

In [ ]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('tensorboard_plot/VGAN_SNAKE.jpg')
plt.figure(figsize=(20,5))
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7fc6a524a2b0>
```



Evaluation on SNAKE

Traing GANs on SNAKE dataset was relatively faster than when on MINIST. That is due to the less complexity of the data. D(x) value when compared to that of the training on MNIST is also better (closer to 0.5) which in turns better reproduction of the input. One thing to note is that due to the different nature of the input, the following functions are not needed:

```
def images_to_vectors(images):
    return images.view(images.size(0), 784)

def vectors_to_images(vectors):
    return vectors.view(vectors.size(0), 1, 28, 28)
```

Task 3.

Use the DCGAN (or an improvement to it) to build a generator for a face image set of your choice.

Can you get realistic faces that are not in the training set?

As always, submit a brief report documenting your experiments and results.

CelebA

Here is a `Logger` class with a lot of useful tricks to indicate training progress and visualize results.

3.1 Set up stuff

In [ ]:

```
import os
import numpy as np
import errno
import torchvision.utils as vutils
from tensorboardX import SummaryWriter
from IPython import display
from matplotlib import pyplot as plt
import torch

'''
    TensorBoard Data will be stored in './runs' path
'''

class Logger:

    def __init__(self, model_name, data_name):
        self.model_name = model_name
        self.data_name = data_name

        self.comment = '{}_{}'.format(model_name, data_name)
        self.data_subdir = '{}/{}'.format(model_name, data_name)

        # TensorBoard
        self.writer = SummaryWriter(comment=self.comment)

    def log(self, d_error, g_error, epoch, n_batch, num_batches):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()

        step = Logger._step(epoch, n_batch, num_batches)
        self.writer.add_scalar(
            '{}/D_error'.format(self.comment), d_error, step)
        self.writer.add_scalar(
            '{}/G_error'.format(self.comment), g_error, step)

    def log_images(self, images, num_images, epoch, n_batch, num_batches, format='NCH
W', normalize=True):
        '''
        input images are expected in format (NCHW)
        '''
        if type(images) == np.ndarray:
            images = torch.from_numpy(images)

        if format=='NHWC':
            images = images.transpose(1,3)


        step = Logger._step(epoch, n_batch, num_batches)
        img_name = '{}/images{}'.format(self.comment, '')

        # Make horizontal grid from image tensor
        horizontal_grid = vutils.make_grid(
            images, normalize=normalize, scale_each=True)
        # Make vertical grid from image tensor
        nrows = int(np.sqrt(num_images))
```

```
        grid = vutils.make_grid(
            images, nrow=nrows, normalize=True, scale_each=True)

        # Add horizontal images to tensorboard
        self.writer.add_image(img_name, horizontal_grid, step)

        # Save plots
        self.save_torch_images(horizontal_grid, grid, epoch, n_batch)

    def save_torch_images(self, horizontal_grid, grid, epoch, n_batch, plot_horizontal=
True):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)

        # Plot and save horizontal
        fig = plt.figure(figsize=(16, 16))
        plt.imshow(np.moveaxis(horizontal_grid.numpy(), 0, -1))
        plt.axis('off')
        if plot_horizontal:
            display.display(plt.gcf())
        self._save_images(fig, epoch, n_batch, 'hori')
        plt.close()

        # Save squared
        fig = plt.figure()
        plt.imshow(np.moveaxis(grid.numpy(), 0, -1))
        plt.axis('off')
        self._save_images(fig, epoch, n_batch)
        plt.close()

    def _save_images(self, fig, epoch, n_batch, comment=''):
        out_dir = './data/images/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        fig.savefig('{}/{}_epoch_{}_batch_{}.png'.format(out_dir,
                                                         comment, epoch, n_batch))

    def display_status(self, epoch, num_epochs, n_batch, num_batches, d_error, g_error,
d_pred_real, d_pred_fake):

        # var_class = torch.autograd.variable.Variable
        if isinstance(d_error, torch.autograd.Variable):
            d_error = d_error.data.cpu().numpy()
        if isinstance(g_error, torch.autograd.Variable):
            g_error = g_error.data.cpu().numpy()
        if isinstance(d_pred_real, torch.autograd.Variable):
            d_pred_real = d_pred_real.data
        if isinstance(d_pred_fake, torch.autograd.Variable):
            d_pred_fake = d_pred_fake.data


        print('Epoch: [{}/{}], Batch Num: [{}/{}]'.format(
            epoch,num_epochs, n_batch, num_batches)
             )
        print('Discriminator Loss: {:.4f}, Generator Loss: {:.4f}'.format(d_error, g_er
ror))
        print('D(x): {:.4f}, D(G(z)): {:.4f}'.format(d_pred_real.mean(), d_pred_fake.me
an()))

    def save_models(self, generator, discriminator, epoch):
```

```
        out_dir = './data/models/{}'.format(self.data_subdir)
        Logger._make_dir(out_dir)
        torch.save(generator.state_dict(),
                   '{}/G_epoch_{}'.format(out_dir, epoch))
        torch.save(discriminator.state_dict(),
                   '{}/D_epoch_{}'.format(out_dir, epoch))

    def close(self):
        self.writer.close()

    # Private Functionality

    @staticmethod
    def _step(epoch, n_batch, num_batches):
        return epoch * num_batches + n_batch

    @staticmethod
    def _make_dir(directory):
        try:
            os.makedirs(directory)
        except OSError as e:
            if e.errno != errno.EEXIST:
                raise
```

In [ ]:

```
def real_data_target(size):
    '''
    Tensor containing ones, with shape = size
    '''
    data = torch.ones(size, 1)
#     if torch.cuda.is_available(): return data.cuda()
    return data.to(device)

def fake_data_target(size):
    '''
    Tensor containing zeros, with shape = size
    '''
    data = torch.zeros(size, 1)
#     if torch.cuda.is_available(): return data.cuda()
    return data.to(device)
```

In [ ]:

```
def train_discriminator(optimizer, real_data, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate real data
    prediction_real = discriminator(real_data)
    error_real = loss(prediction_real, real_data_target(real_data.size(0)))
    error_real.backward()

    # Propagate fake data
    prediction_fake = discriminator(fake_data)
    error_fake = loss(prediction_fake, fake_data_target(real_data.size(0)))
    error_fake.backward()

    # Take a step
    optimizer.step()

    # Return error
    return error_real + error_fake, prediction_real, prediction_fake
```

And here's a function for a single step of the generator:

In [ ]:

```
def train_generator(optimizer, fake_data):
    # Reset gradients
    optimizer.zero_grad()

    # Propagate the fake data through the discriminator and backpropagate.
    # Note that since we want the generator to output something that gets
    # the discriminator to output a 1, we use the real data target here.
    prediction = discriminator(fake_data)
    error = loss(prediction, real_data_target(prediction.size(0)))
    error.backward()

    # Update weights with gradients
    optimizer.step()

    # Return error
    return error
```

Configure Device available

In [ ]:

```
device = torch.device('cuda:3') if torch.cuda.is_available() else torch.device("cpu")
print("Configured device: ", device)
```

```
Configured device:  cuda:3
```

Generate test noise samples

Let's generate some noise vectors to use as inputs to the generator. We'll use these samples repeatedly to see the evolution of the generator over time.

In [ ]:

```
# generate size vectors with 100 features
def noise(size):
    n = torch.randn(size, 100) # mean = 0, std = 1
    return n.to(device)

num_test_samples = 16
test_noise = noise(num_test_samples)
```

3.2 DCGAN for FACE

3.3 Load Labeled Faces in the Wild Home data

For our DCGAN experiment, we'll use FACE.

3.3.1 Load image

In [ ]:

```
import torch
from torch import nn, optim
from torchvision import transforms, datasets
from PIL import Image

import torch
from torch import nn, optim
from torchvision import transforms, datasets
```

In [ ]:

```
import torchvision
from torch.utils.data import DataLoader, Dataset, TensorDataset
from torchvision import transforms, datasets
#transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),

compose = transforms.Compose(
    [
        transforms.Resize(64),
        transforms.ToTensor(),
        transforms.Normalize((.5, .5, .5), (.5, .5, .5))
    ])

data = torchvision.datasets.ImageFolder(root='./lfw-deepfunneled/', transform=compose)

batch_size = 256
data_loader = torch.utils.data.DataLoader(data, batch_size=batch_size, shuffle=True)

num_batches = len(data_loader)
print(num_batches)
```

```
52
```

3.4 Network architechture

In [ ]:

```
#NO BIASES BECAUSE BATCHNORM!!!
class DiscriminativeNet(torch.nn.Module):

    def __init__(self):
        super(DiscriminativeNet, self).__init__()

        self.conv1 = nn.Sequential(
            nn.Conv2d(
                in_channels=3, out_channels=128, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(
                in_channels=128, out_channels=256, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv3 = nn.Sequential(
            nn.Conv2d(
                in_channels=256, out_channels=512, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.conv4 = nn.Sequential(
            nn.Conv2d(
                in_channels=512, out_channels=1024, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(1024),
            nn.LeakyReLU(0.2, inplace=True)
        )
        self.out = nn.Sequential(
            nn.Linear(1024*4*4, 1),
            nn.Sigmoid(),
        )

    def forward(self, x):
        # Convolutional layers
        x = self.conv1(x)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.conv4(x)
        # Flatten and apply sigmoid
        x = x.view(-1, 1024*4*4)
        x = self.out(x)
        return x
```

The generator is using transpose convolutions with batch normalization:

In [ ]:

```
class GenerativeNet(torch.nn.Module):

    def __init__(self):
        super(GenerativeNet, self).__init__()

        self.linear = torch.nn.Linear(100, 1024*4*4)

        self.conv1 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=1024, out_channels=512, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True)
        )
        self.conv2 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=512, out_channels=256, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True)
        )
        self.conv3 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=256, out_channels=128, kernel_size=4,
                stride=2, padding=1, bias=False
            ),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True)
        )
        self.conv4 = nn.Sequential(
            nn.ConvTranspose2d(
                in_channels=128, out_channels=3, kernel_size=4,
                stride=2, padding=1, bias=False
            )
        )
        self.out = torch.nn.Tanh()

    def forward(self, x):
        # Project and reshape
        x = self.linear(x)
        x = x.view(x.shape[0], 1024, 4, 4)
        # Convolutional layers
        x = self.conv1(x)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.conv4(x)
        # Apply Tanh
        return self.out(x)
```

Let's create a generator and discriminator and initialize their weights:

In [ ]:

```
# Custom weight initialization

def init_weights(m):
    classname = m.__class__.__name__
    if classname.find('Conv') != -1 or classname.find('BatchNorm') != -1:
        m.weight.data.normal_(0.00, 0.02)

# Instantiate networks

generator = GenerativeNet()
generator.apply(init_weights)
discriminator = DiscriminativeNet()
discriminator.apply(init_weights)


# Enable cuda if available

if torch.cuda.is_available():
    generator.cuda(device)
    discriminator.cuda(device)
```

3.5 Optimizers and loss function

Next, we set up the optimizers and loss function.

In [ ]:

```
# Optimizers

d_optimizer = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
g_optimizer = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))

# Loss function

loss = nn.BCELoss()

# Number of epochs of training
num_epochs = 200
```

3.5 Optimizers and loss function

Next, we set up the optimizers and loss function.

In [ ]:

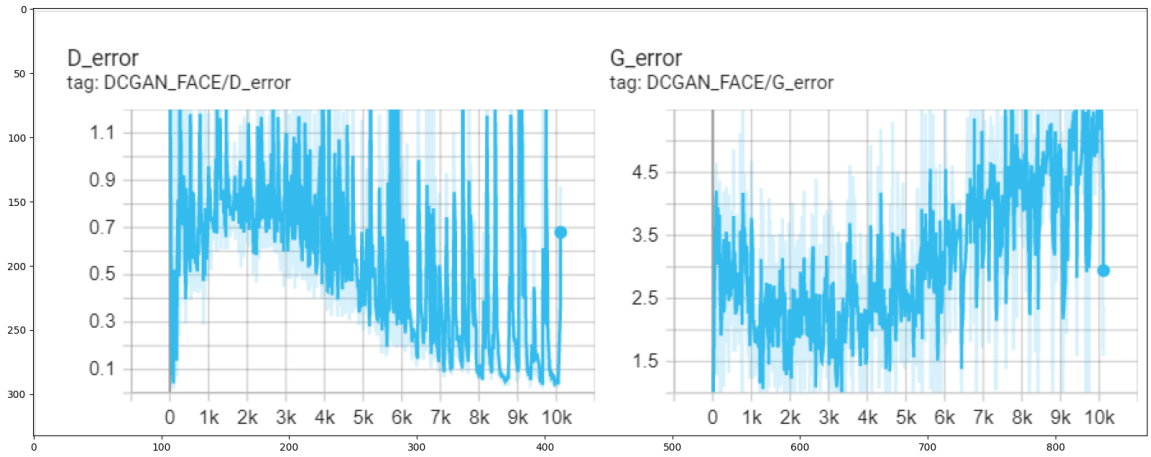
```
num_test_samples = 16
test_noise = noise(num_test_samples)
num_epochs = 200

logger = Logger(model_name='DCGAN', data_name='FACE')

for epoch in range(num_epochs):
    for n_batch, (real_data,_) in enumerate(data_loader):

        # Train Discriminator

        if torch.cuda.is_available(): real_data = real_data.cuda(device)
        fake_data = generator(noise(real_data.size(0))).detach()
        d_error, d_pred_real, d_pred_fake = train_discriminator(d_optimizer,
                                                                real_data, fake_data)

        # Train Generator

        fake_data = generator(noise(real_data.size(0)))
        g_error = train_generator(g_optimizer, fake_data)

        # Log error and display progress
        logger.log(d_error, g_error, epoch, n_batch, num_batches)
        if (n_batch) % 100 == 0:
            display.clear_output(True)
            # Display Images
            test_images = generator(test_noise).data.cpu()
            logger.log_images(test_images, num_test_samples, epoch, n_batch, num_batche
s);
            # Display status Logs
            logger.display_status(
                epoch, num_epochs, n_batch, num_batches,
                d_error, g_error, d_pred_real, d_pred_fake
            )

        # Save model checkpoints
        logger.save_models(generator, discriminator, epoch)
```

```
Epoch: [194/200], Batch Num: [0/52]
Discriminator Loss: 0.9746, Generator Loss: 1.2751
D(x): 0.6655, D(G(z)): 0.3726
```

In [ ]:

```
%pylab inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('tensorboard_plot/DCGAN_FACE.png')
plt.figure(figsize = (20,10))
imgplot = plt.imshow(img)
plt.show()
```

```
%pylab is deprecated, use %matplotlib inline and import the required libra
ries.
Populating the interactive namespace from numpy and matplotlib
```



Evaluation on FACE

Traing GANs on SNAKE dataset does not produce as positive results as others. That maybe due to not enough number of epochs. The number of epochs in this training is 50 which results in D(x) to be at 0.9438 which is still far off the optimal value which is 0.5.

One important thing i learnt is how to use '.npz' file and how to convert it to PIL image in order to use the image folder before loading the data into the loader.