Deep Learning: Assignment-8

Train a GAN Model on any dataset

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Importing the libraries

```
from __future__ import print_function
import time
import torch
import torch.nn as nn
import torch.nn.parallel
import torch.optim as optim
import torch.utils.data
import torchvision.datasets as dset
import torchvision.transforms as transforms
import torchvision.utils as vutils
from torch.autograd import Variable
import matplotlib.pyplot as plt
import numpy as np
from torch import nn, optim
import torch.nn.functional as F
from torchvision import datasets, transforms
from torchvision.utils import save_image
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from tqdm import tqdm_notebook as tqdm
```

For this assignment, We've used The Stanford Dogs dataset Context

The Stanford Dogs dataset contains images of 120 breeds of dogs from around the world. This dataset has been built using images and annotation from ImageNet for the task of fine-grained image categorization. It was originally collected for fine-grain image categorization, a challenging problem as certain dog breeds have near identical features or differ in colour and age.

Content:

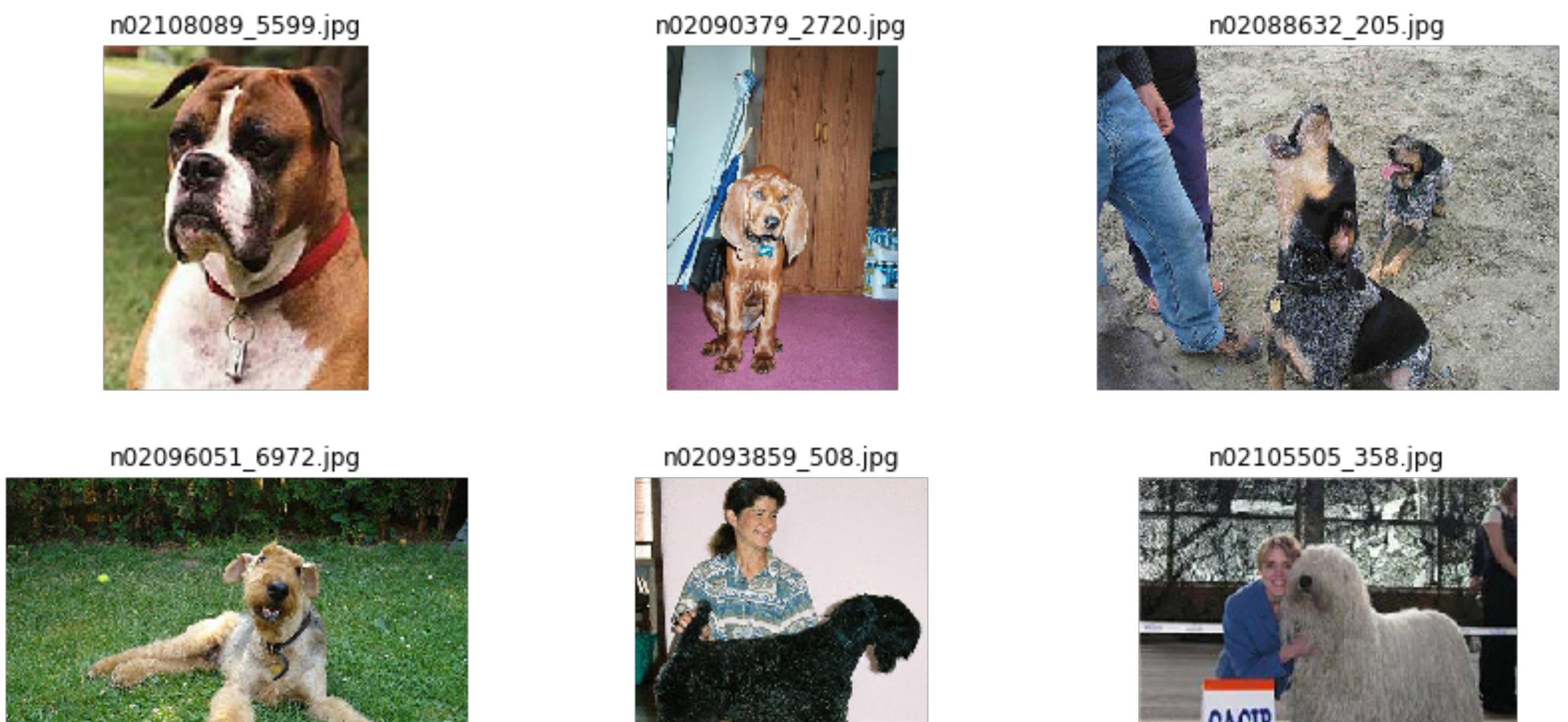
Number of categories: 120

Number of images: 20,580

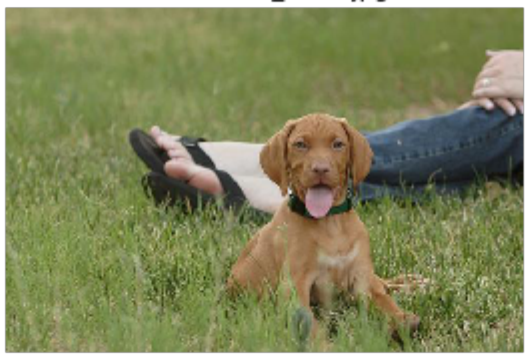
Annotations: Class labels, Bounding boxes

```
PATH = '../input/all-dogs/all-dogs/'
images = os.listdir(PATH)
print(f'There are {len(os.listdir(PATH))} pictures of dogs.')

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(12,10))

for indx, axis in enumerate(axes.flatten()):
    rnd_indx = np.random.randint(0, len(os.listdir(PATH)))
    img = plt.imread(PATH + images[rnd_indx])
    imgplot = axis.imshow(img)
    axis.set_title(images[rnd_indx])
    axis.set_axis_off()
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```

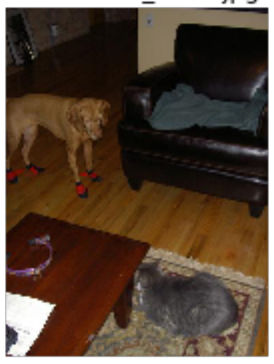
```
There are 20579 pictures of dogs.
```



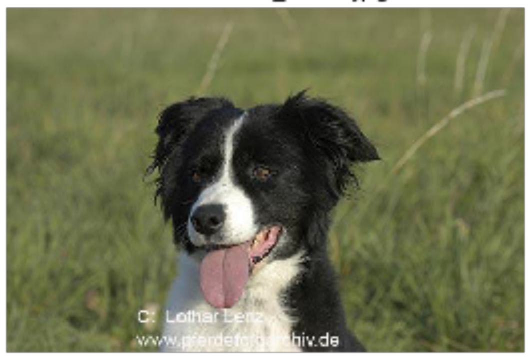
n02100583_1560.jpg



n02100583_6040.jpg



n02106166_1205.jpg



Pre-processing the images in the dataset

```python
batch_size = 32
image_size = 64

random_transforms = [transforms.ColorJitter(), transforms.RandomRotation(degrees=20)]
transform = transforms.Compose([transforms.Resize(64),
                                transforms.CenterCrop(64),
                                transforms.RandomHorizontalFlip(p=0.5),
                                transforms.RandomApply(random_transforms, p=0.2),
                                transforms.ToTensor(),
                                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

train_data = datasets.ImageFolder('../input/all-dogs/', transform=transform)
train_loader = torch.utils.data.DataLoader(train_data, shuffle=True,
                                           batch_size=batch_size)

imgs, label = next(iter(train_loader))
imgs = imgs.numpy().transpose(0, 2, 3, 1)
```

Initial Results

Defining the Weights

```python
def weights_init(m):
    """
    Takes as input a neural network m that will initialize all its weights.
    """
    classname = m.__class__.__name__
    if classname.find('Conv') != -1:
        m.weight.data.normal_(0.0, 0.02)
    elif classname.find('BatchNorm') != -1:
        m.weight.data.normal_(1.0, 0.02)
        m.bias.data.fill_(0)
```

Generator

```python
class G(nn.Module):
    def __init__(self):
        # Used to inherit the torch.nn Module
        super(G, self).__init__()
        # Meta Module - consists of different layers of Modules
        self.main = nn.Sequential(
                nn.ConvTranspose2d(100, 512, 4, stride=1, padding=0, bias=False),
                nn.BatchNorm2d(512),
                nn.ReLU(True),
                nn.ConvTranspose2d(512, 256, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(256),
                nn.ReLU(True),
                nn.ConvTranspose2d(256, 128, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(128),
                nn.ReLU(True),
                nn.ConvTranspose2d(128, 64, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(64),
                nn.ReLU(True),
                nn.ConvTranspose2d(64, 3, 4, stride=2, padding=1, bias=False),
                nn.Tanh()
                )

    def forward(self, input):
        output = self.main(input)
        return output

```

```
# Creating the generator
netG = G()
netG.apply(weights_init)
```

```
G(
  (main): Sequential(
    (0): ConvTranspose2d(100, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace)
    (3): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (4): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): ReLU(inplace)
    (6): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (7): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): ReLU(inplace)
    (9): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): ReLU(inplace)
    (12): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (13): Tanh()
  )
)
```

Discriminator

```
# Defining the discriminator
class D(nn.Module):
    def __init__(self):
        super(D, self).__init__()
        self.main = nn.Sequential(
                nn.Conv2d(3, 64, 4, stride=2, padding=1, bias=False),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(64, 128, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(128),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(128, 256, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(256),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(256, 512, 4, stride=2, padding=1, bias=False),
                nn.BatchNorm2d(512),
                nn.LeakyReLU(negative_slope=0.2, inplace=True),
                nn.Conv2d(512, 1, 4, stride=1, padding=0, bias=False),
                nn.Sigmoid()
                )

    def forward(self, input):
        output = self.main(input)
        # .view(-1) = Flattens the output into 1D instead of 2D
        return output.view(-1)


# Creating the discriminator
netD = D()
netD.apply(weights_init)

```

```
D(
  (main): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): LeakyReLU(negative_slope=0.2, inplace)
    (2): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (4): LeakyReLU(negative_slope=0.2, inplace)
    (5): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (7): LeakyReLU(negative_slope=0.2, inplace)
    (8): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (9): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (10): LeakyReLU(negative_slope=0.2, inplace)
    (11): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (12): Sigmoid()
  )
)
```

Training Parameters

```
batch_size = 32
LR_G = 0.001
LR_D = 0.0005

beta1 = 0.5
epochs = 100

real_label = 0.9
```

```
fake_label = 0
nz = 128

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

Initialize models and optimizers

```
netG = Generator(nz).to(device)
netD = Discriminator().to(device)

criterion = nn.BCELoss()

optimizerD = optim.Adam(netD.parameters(), lr=LR_D, betas=(beta1, 0.999))
optimizerG = optim.Adam(netG.parameters(), lr=LR_G, betas=(beta1, 0.999))

fixed_noise = torch.randn(25, nz, 1, 1, device=device)

G_losses = []
D_losses = []
epoch_time = []
```

```
def plot_loss (G_losses, D_losses, epoch):
    plt.figure(figsize=(10,5))
    plt.title("Generator and Discriminator Loss - EPOCH "+ str(epoch))
    plt.plot(G_losses,label="G")
    plt.plot(D_losses,label="D")
    plt.xlabel("iterations")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
```

Show generated images

```
def show_generated_img(n_images=5):
    sample = []
    for _ in range(n_images):
        noise = torch.randn(1, nz, 1, 1, device=device)
        gen_image = netG(noise).to("cpu").clone().detach().squeeze(0)
        gen_image = gen_image.numpy().transpose(1, 2, 0)
        sample.append(gen_image)

    figure, axes = plt.subplots(1, len(sample), figsize = (64,64))
    for index, axis in enumerate(axes):
        axis.axis('off')
        image_array = sample[index]
        axis.imshow(image_array)

    plt.show()
    plt.close()
```

Training Loop

```
for epoch in range(epochs):

    start = time.time()
    for ii, (real_images, train_labels) in tqdm(enumerate(train_loader), total=len(train_loader)):
        ############################
        # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
        ###########################
        # train with real
        netD.zero_grad()
        real_images = real_images.to(device)
        batch_size = real_images.size(0)
        labels = torch.full((batch_size, 1), real_label, device=device)

        output = netD(real_images)
        errD_real = criterion(output, labels)
        errD_real.backward()
        D_x = output.mean().item()

        # train with fake
        noise = torch.randn(batch_size, nz, 1, 1, device=device)
        fake = netG(noise)
        labels.fill_(fake_label)
        output = netD(fake.detach())
        errD_fake = criterion(output, labels)
        errD_fake.backward()
        D_G_z1 = output.mean().item()
        errD = errD_real + errD_fake
        optimizerD.step()
```

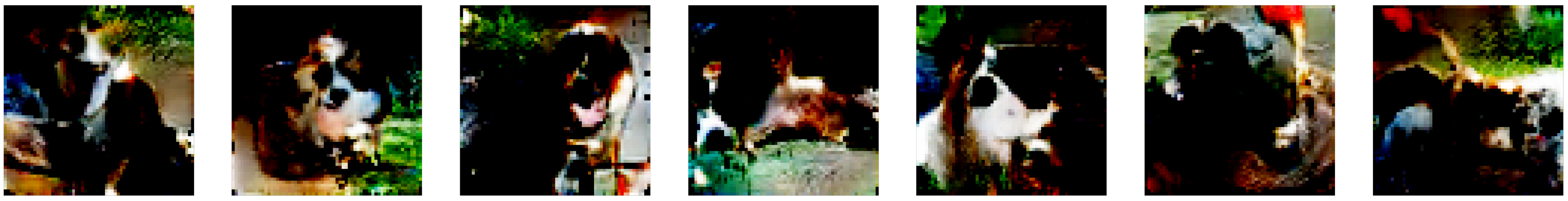
```python

        ############################
        # (2) Update G network: maximize log(D(G(z)))
        ###########################
        netG.zero_grad()
        labels.fill_(real_label)  # fake labels are real for generator cost
        output = netD(fake)
        errG = criterion(output, labels)
        errG.backward()
        D_G_z2 = output.mean().item()
        optimizerG.step()

        # Save Losses for plotting later
        G_losses.append(errG.item())
        D_losses.append(errD.item())

        if (ii+1) % (len(train_loader)//2) == 0:
            print('[%d/%d][%d/%d] Loss_D: %.4f Loss_G: %.4f D(x): %.4f D(G(z)): %.4f / %.4f'
                  % (epoch + 1, epochs, ii+1, len(train_loader),
                     errD.item(), errG.item(), D_x, D_G_z1, D_G_z2))

    plot_loss (G_losses, D_losses, epoch)
    G_losses = []
    D_losses = []
    if epoch % 10 == 0:
        show_generated_img()

    epoch_time.append(time.time()- start)

#             valid_image = netG(fixed_noise)
```

```python
print (">> average EPOCH duration = ", np.mean(epoch_time))
```

```
>> average EPOCH duration =  121.24567284107208
```

Generated Images

```python
show_generated_img(7)
```



```python
fig = plt.figure(figsize=(25, 16))
# display 10 images from each class
for i, j in enumerate(images[:32]):
    ax = fig.add_subplot(4, 8, i + 1, xticks=[], yticks=[])
    plt.imshow(j)
```