

```
%pylab inline
!pip install -q gdown httpimport
!pip install wandb --upgrade
!pip install fastai --upgrade
!pip install torch==1.9.0

import wandb
wandb.login()

# from google.colab import drive
# drive.mount('/content/drive')
import matplotlib.pyplot as plt
import numpy as np
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torch.distributions import MultivariateNormal, Uniform
from torch.utils.data import DataLoader, Dataset
from torchvision.transforms import Compose
from torchvision import transforms
from torchvision import datasets
import collections
from PIL import Image

device = 'cuda'
```

▼ Utils

▼ config

```
config = dict(
    epochs=100,
    batch_size=64,
    img_size=256,
    G_lr=0.001,
    C_lr=0.0001,
    lambda_=1.,
    wass_alpha = 1.,
    log_every=50,
    data_dir='../input',
    dataset='landscapes',
    dataset_in_rgb = True,
    architecture='GAN',
    device='cuda',
)
```

▼ data loader

with simple data augmentation

We work only with 256x256 pictures because of the architecture of our network.

```
from skimage import color

def transform_img(x, imsize, lab=True):
    pre_trans = transforms.Compose([
        transforms.ToTensor(),
        transforms.Resize([int(imsize*1.2), int(imsize*1.2)]),
        transforms.RandomAffine(degrees=25, scale=(1.,1.1)),
        transforms.CenterCrop(imsize),
        transforms.Resize([imsize, imsize]),
        transforms.RandomHorizontalFlip(),
    ])
    x = pre_trans(x)
    if lab:
        x = color.rgb2lab(x.permute(1,2,0))
        x = transforms.ToTensor()(x)
    return x

def get_data(imsize = 256, batch_size = 64, data_dir = None, lab=True):
    # ImageFolder with root directory and defined transformation methods for batch as well
    data = datasets.ImageFolder(root=data_dir, transform = lambda x: transform_img(x, imsize, lab=lab))
    data_loader = DataLoader(dataset=data, batch_size=batch_size, shuffle=True, num_workers=4)

    return data_loader

def get_img(path, imsize=256,lab=True):
    im = Image.open(path)
    return transform_img(im, imsize,lab=lab)
```

▼ rgb <-> lab

differentiable conversion between formats in pytorch

```
'''
NOW WORKS FOR BATCHES!
adapted code from
https://github.com/smartcameras/EdgeFool/blob/master/Train/rgb\_lab\_formulation\_pytorch.py
'''
```

```
def rgb_to_lab(srrgb):

    srrgb = srrgb.permute(0, 2, 3, 1).cuda()
    srrgb_pixels = torch.reshape(srrgb, [srrgb.size(0), -1, 3])

    linear_mask = (srrgb_pixels <= 0.04045).type(torch.FloatTensor).cuda()
    exponential_mask = (srrgb_pixels > 0.04045).type(torch.FloatTensor).cuda()
```

```

exponential_mask = (srgb_pixels / 12.92 * linear_mask).type(torch.FloatTensor).cuda()
srgb_pixels = (srgb_pixels / 12.92 * linear_mask) + (((srgb_pixels + 0.055) / 1.055) **

rgb_to_xyz = torch.tensor([
    #      X      Y      Z
    [0.412453, 0.212671, 0.019334], # R
    [0.357580, 0.715160, 0.119193], # G
    [0.180423, 0.072169, 0.950227], # B
]).type(torch.FloatTensor).cuda()

xyz_pixels = torch.matmul(rgb_pixels, rgb_to_xyz)

# XYZ to Lab
xyz_normalized_pixels = torch.mul(xyz_pixels, torch.tensor([1/0.950456, 1.0, 1/1.08875

epsilon = 6.0/29.0

linear_mask = (xyz_normalized_pixels <= (epsilon**3)).type(torch.FloatTensor).cuda()

exponential_mask = (xyz_normalized_pixels > (epsilon**3)).type(torch.FloatTensor).cuda

fxfyfz_pixels = (xyz_normalized_pixels / (3 * epsilon**2) + 4.0/29.0) * linear_mask +
# convert to lab
fxfyfz_to_lab = torch.tensor([
    #  l      a      b
    [ 0.0,  500.0,   0.0], # fx
    [116.0, -500.0,  200.0], # fy
    [ 0.0,   0.0, -200.0], # fz
]).type(torch.FloatTensor).cuda()
lab_pixels = torch.matmul(fxfyfz_pixels, fxfyfz_to_lab) + torch.tensor([-16.0, 0.0, 0.
#return tf.reshape(lab_pixels, tf.shape(srgb))
return torch.reshape(lab_pixels, srgb.shape).permute(0, 3, 1, 2)

def lab_to_rgb(lab):
    lab = lab.permute(0, 2, 3, 1).cuda()
    lab_pixels = torch.reshape(lab, [lab.size(0), -1, 3])
    # convert to fxfyfz
    lab_to_fxfyfz = torch.tensor([
        #  fx      fy      fz
        [1/116.0, 1/116.0,  1/116.0], # l
        [1/500.0,   0.0,   0.0], # a
        [ 0.0,   0.0, -1/200.0], # b
    ]).type(torch.FloatTensor).cuda()
    fxfyfz_pixels = torch.matmul(lab_pixels + torch.tensor([16.0, 0.0, 0.0])).type(torch.Fl

# convert to xyz
epsilon = 6.0/29.0
linear_mask = (fxfyfz_pixels <= epsilon).type(torch.FloatTensor).cuda()
exponential_mask = (fxfyfz_pixels > epsilon).type(torch.FloatTensor).cuda()

xyz_pixels = (3 * epsilon**2 * (fxfyfz_pixels - 4/29.0)) * linear_mask + ((fxfyfz_pixe

# denormalize for D65 white point
xyz_pixels = torch.mul(xyz_pixels, torch.tensor([0.950456, 1.0, 1.088754])).type(torch.

```

```

xyz_to_rgb = torch.tensor([
    #      r      g      b
    [ 3.2404542, -0.9692660,  0.0556434], # x
    [-1.5371385,  1.8760108, -0.2040259], # y
    [-0.4985314,  0.0415560,  1.0572252], # z
]).type(torch.FloatTensor).cuda()

rgb_pixels = torch.matmul(xyz_pixels, xyz_to_rgb)
# avoid a slightly negative number messing up the conversion
#clip
rgb_pixels[rgb_pixels > 1] = 1.
rgb_pixels[rgb_pixels < 0] = 0.

linear_mask = (rgb_pixels <= 0.0031308).type(torch.FloatTensor).cuda()
exponential_mask = (rgb_pixels > 0.0031308).type(torch.FloatTensor).cuda()
srgb_pixels = (rgb_pixels * 12.92 * linear_mask) + (((rgb_pixels+0.000001) ** (1/2.4))

return torch.reshape(srgb_pixels, lab.shape).permute(0, 3, 1, 2)

```

▼ show img

```

def show_img_gen(img, img_col = None, show= True):
    with torch.no_grad():
        if img_col is not None:
            img = torch.cat([img.cpu(), img_col.cpu()], 0)
            img = color.lab2rgb(img.cpu().permute(1,2,0))
        if show:
            plt.imshow(img)
            plt.show()
        else:
            return img

```

▼ Net architecture

▼ UNet Block

```

...
Net architecture from
https://towardsdatascience.com/colorizing-black-white-images-with-u-net-and-conditional-ga
same story for Critic
...

class UnetBlock(nn.Module):
    def __init__(self, nf, ni, submodule=None, input_c=None, dropout=False,
                 innermost=False, outermost=False):

```

```

super().__init__()
self.outermost = outermost
if input_c is None: input_c = nf
downconv = nn.Conv2d(input_c, ni, kernel_size=4,
                      stride=2, padding=1, bias=False)
downrelu = nn.LeakyReLU(0.2, True)
downnorm = nn.BatchNorm2d(ni)
uprelu = nn.ReLU(True)
upnorm = nn.BatchNorm2d(nf)

if outermost:
    upconv = nn.ConvTranspose2d(ni * 2, nf, kernel_size=4,
                                stride=2, padding=1)

    down = [downconv]
    # up = [uprelu, upconv, nn.Tanh()]
    up = [uprelu, upconv] #remove tanh - accelerates learning!
    model = down + [submodule] + up
elif innermost:
    upconv = nn.ConvTranspose2d(ni, nf, kernel_size=4,
                                stride=2, padding=1, bias=False)

    down = [downrelu, downconv]
    up = [uprelu, upconv, upnorm]
    model = down + up
else:
    upconv = nn.ConvTranspose2d(ni * 2, nf, kernel_size=4,
                                stride=2, padding=1, bias=False)

    down = [downrelu, downconv, downnorm]
    up = [uprelu, upconv, upnorm]
    if dropout: up += [nn.Dropout(0.5)]
    model = down + [submodule] + up
self.model = nn.Sequential(*model)

def forward(self, x):
    if self.outermost:
        return self.model(x)
    else:
        return torch.cat([x, self.model(x)], 1)

```

▼ Generator

```

class TheGenerator(nn.Module):
    def __init__(self, input_c=1, output_c=2, n_down=8, num_filters=64):
        super().__init__()
        unet_block = UnetBlock(num_filters * 8, num_filters * 8, innermost=True)

        for _ in range(n_down - 4):
            unet_block = UnetBlock(num_filters * 8, num_filters * 8, submodule=unet_block,
                                   out_filters = num_filters * 8)

        for _ in range(2):
            unet_block = UnetBlock(out_filters // 2, out_filters, submodule=unet_block)
            out_filters //= 2

```

```

        out_filters //= 2
    self.model = UnetBlock(output_c, out_filters, input_c=input_c, submodule=unet_block)

def forward(self, x):
    return self.model(x)

```

▼ Critic

Trick! - Critic divides the picture into batches and categorizes each of them independently. It seems to make sense since the validity of the coloring task is kind of local. It also give more information to the Generator.

```

class Critic(nn.Module):
    def __init__(self, input_c=3, nf=64, n_down=3):
        super(Critic, self).__init__()
        model = [self.get_layers(input_c, nf, norm=False)]
        model += [self.get_layers(nf * 2 ** i, nf * 2 ** (i + 1), s=1 if i == (n_down-1) else 2
                                for i in range(n_down))] # the 'if' statement is taking care of n
                                                         # stride of 2 for the last block in this
        model += [self.get_layers(nf * 2 ** n_down, 1, s=1, norm=False, act=False)] # Make

        model += [nn.Sigmoid()] # seems reasonable
        self.model = nn.Sequential(*model)

    def get_layers(self, ni, nf, k=4, s=2, p=1, norm=True, act=True): # when needing to make
        layers = [nn.Conv2d(ni, nf, k, s, p, bias=not norm)] # it's always helpful
        if norm: layers += [nn.BatchNorm2d(nf)]
        if act: layers += [nn.LeakyReLU(0.2, True)]
        return nn.Sequential(*layers)

    def forward(self, x):
        return self.model(x)

```

▼ losses

```

def generator_loss(DG, eps=1e-6):
    # Define Generator loss. Use eps for numerical stability of log.
    return - (DG + eps).log().mean()

def img_l1_loss(img_fake, img_real):
    return nn.L1Loss()(img_fake, img_real)

def critic_loss(DR, DG, eps=1e-6):
    # Define Discriminator loss. Use eps for numerical stability of log.
    return - (DR + eps).log().mean() - (1 - DG + eps).log().mean()

```

▼ wass l2 loss

An interesting one. We wanted to extract style of an image using pretrained vgg network (as we did in Assignment 3) but instead of using the mean squared network between styles of two pictures we wanted to do something more clever. We apply an Earth Mover Distance/ Wasserstein Distance assuming our features have gaussian distribution (we 'sample' across channel dimension, independently for each element of the batch). Interestingly it is stated that the required computation is not too heavy (arguably).

The math is here https://github.com/VinceMarron/style_transfer/blob/master/style-transfer-theory.pdf

```
import torchvision.models as models
import torch
import torch.linalg

class WassFeatureLoss(nn.Module):
    def __init__(self):
        super().__init__()
        self.vgg_features = models.vgg19(True).features.cuda().eval()
        self.RGB_MEANS = torch.FloatTensor([0.485, 0.456, 0.406])[None, :, None, None].cuda
        self.RGB_STDS = torch.FloatTensor([0.229, 0.224, 0.225])[None, :, None, None].cuda

    def _get_features(self, x, clone=False):
        x = (x - torch.autograd.Variable(self.RGB_MEANS)) / torch.autograd.Variable(self.RGB_STDS)
        x = self.vgg_features(x)
        x = x.view(x.size(0), x.size(1), -1)
        return x.clone() if clone else x

    def _calc_2_moments(self, tensor): #bs x chans x n -> bs x chans x chans
        n = tensor.shape[2]
        mu = tensor.mean(2)
        tensor = (tensor - mu[:, :, None])
        # Prevents nasty bug that happens very occassionally- divide by zero. Why such th
        if n == 0:
            return None, None
        # TODO: ROOM FOR IMPROVEMENT BELOW
        cov = torch.vstack([torch.matmul(tens, tens.t()).unsqueeze(0) for tens in tensor])
        return mu, cov

    def _calc_l2wass_dist(self, mu1, cov1, mu2, cov2): # bs x chans ; bs x chans x chans
        mean_diff_squared = (mu1 - mu2).pow(2).sum(1) # bs
        bs = mu1.size(0)
        var_overlap = torch.zeros(bs, device=device)
        var_components = torch.zeros(bs, device=device)
        for i in range(bs):
            cov1_flat, cov2_flat = cov1[i], cov2[i]
            eigvals1, eigvecs1 = torch.linalg.eigh(cov1_flat)
            eigroot_mat1 = torch.diag(torch.sqrt(eigvals1.clamp(min=0)))
            root_cov1 = torch.mm(torch.mm(eigvecs1, eigroot_mat1), eigvecs1.t())
            cov_prod = torch.mm(torch.mm(root_cov1, cov2_flat), root_cov1)
```

```

tr_cov2 = torch.linalg.eigh(cov2)[0].clamp(min=1e-5).sum()
tr_cov1 = eigvals1.clamp(min=1e-5).sum()
var_components[i] = tr_cov1 + tr_cov2
var_overlap[i] = torch.sqrt(
    torch.linalg.eigh(cov_prod)[0].clamp(min=0) + 1e-8
).sum()

return (mean_diff_squared + var_components - 2 * var_overlap).sqrt()

def forward(self, x, y):
    x_feat = self._get_features(x.to(device))
    y_feat = self._get_features(y.to(device), clone=True)

    x_mu, x_cov = self._calc_2_moments(x_feat)
    y_mu, y_cov = self._calc_2_moments(y_feat)

    dist = self._calc_l2wass_dist(x_mu, x_cov, y_mu, y_cov)

    return dist.mean()

```

▼ Let's go

▼ init

```

def make(config):
    img_dl = get_data(config.img_size, batch_size=config.batch_size, data_dir=config.data_

    G = TheGenerator().to(config.device)
    C = Critic().to(config.device)

    G_optimizer = optim.Adam(G.parameters(), lr=config.G_lr)
    C_optimizer = optim.Adam(C.parameters(), lr=config.C_lr)

    return G, C, G_optimizer, C_optimizer, img_dl

```

▼ training loop

Copy-pasted from Assignment 5 Here we have GAN conditioned on black-and-white picture. Generator's goal is to color it so that Discriminator can't distinguish real pictures from fake ones.

```

def train(G, C, img_dl, G_optimizer, C_optimizer, config):
    wandb.watch(G, log="all", log_freq=5)
    wandb.watch(C, log="all", log_freq=5)
    wass_l2_dist = WassFeatureLoss()
    G_loss = 0.0
    C_loss = 0.0
    for epoch in range(config.epochs):

```



```

start_time = time.time()

for i, (img_real_rgb, _) in enumerate(img_dl):
    #pictures are ALWAYS in shape (bs, 3, ims, ims)
    img_real_lab = rgb_to_lab(img_real_rgb).to(config.device).requires_grad_()
    img_bw = img_real_lab[:,0,:,:].unsqueeze(1)

    img_fake_lab = torch.cat([img_bw, G(img_bw)], 1)
    img_fake_rgb = lab_to_rgb(img_fake_lab.clamp(min=-110.,max=110.))

    img_fake_detached = img_fake_lab.detach()

    if True: #i % config.log_every == 0 and i>0:
        G.eval()
        with torch.no_grad():
            print(
                f"Epoch: {epoch} i: {i} Generator loss: {G_loss :.4f} Critic loss: {
            )
            fig = plt.figure(figsize=(20, 8))
            for j in range(5):
                fig.add_subplot(2, 5, 1 + j)
                plt.axis('off')
                plt.imshow(show_img_gen(img_fake_lab[j],show = False))
            for j in range(5):
                fig.add_subplot(2, 5, 6 + j)
                plt.axis('off')
                plt.imshow(show_img_gen(img_real_lab[j],show = False))
            plt.show()
            wandb.log({
                'G_loss': G_loss,
                'C_loss': C_loss,
                'generated_imgs': [wandb.Image(color.lab2rgb(img.cpu()).permute(1,2
                'original_imgs': [wandb.Image(color.lab2rgb(img.cpu()).permute(1,2,
            })

            G_loss = 0.0
            C_loss = 0.0
            G.train()

wass = wass_l2_dist(img_fake_rgb, img_real_rgb)
l1 = img_l1_loss(img_fake_lab, img_real_lab)

G_loss = generator_loss(C(img_fake_lab)) \
    + config.lambda_ * l1 \
    + config.wass_alpha * wass

G_optimizer.zero_grad()
G_loss.backward()
torch.nn.utils.clip_grad_norm_(G.parameters(), 1e4)
G_optimizer.step()

C_loss = critic_loss(C(img_real_lab), C(img_fake_detached))

C_optimizer.zero_grad()
C_loss.backward()

```

```

        C_optimizer.step()

    G_loss += G_loss.item()
    C_loss += C_loss.item()

    delta = int(time.time() - start_time)
    print(f"Finished epoch {epoch} in {delta//60}min {delta % 60}s")
    if epoch % 10 == 0 and epoch > 0:
        print(f"saving models..")
        save_models(G, C, G_path=f'generator_{epoch}.pth', C_path=f'critic_{epoch}.pth')

```

▼ W&B requirement

We use an interesting tool helping with data visualisation and compute management called Weights & Biases. More here: <https://wandb.ai/>

```

def model_pipeline(params, saved_G=None, saved_C=None):
    with wandb.init(entity="colorify", project="colorify", config=params):
        config = wandb.config
        G, C, G_optimizer, C_optimizer, img_dl = make(config)
        if saved_G is not None:
            G = saved_G
        if saved_C is not None:
            C = saved_C
        train(G, C, img_dl, G_optimizer, C_optimizer, config)
        # imgs = get_imgs(G)

        torch.onnx.export(G, next(iter(img_dl))[0][:,0,None].to(config.device).float(), "G"
            wandb.save("G.onnx")

        torch.onnx.export(C, next(iter(img_dl))[0].to(config.device).float(), "C.onnx")
            wandb.save("C.onnx")

    return G, C

```

▼ save/load model

```

def save_models(G, C, G_path='generator.pth', C_path='critic.pth'):
    torch.save(G.state_dict(), G_path)
    torch.save(C.state_dict(), C_path)

def load_models(G, C, G_path='generator.pth', C_path='critic.pth'):
    G.load_state_dict(torch.load(G_path))
    C.load_state_dict(torch.load(C_path))

G = TheGenerator().to(device)
C = Critic().to(device)
load_models(G, C, G_path='./checkpoint4/generator_210_aug_3.pth', C_path='./checkpoint4/cr

```

▼ start!

```
G, C = model_pipeline(config)
```

▼ Results

▼ show results

```
def show_results(net_names, dataset_name, num_images):
    G = TheGenerator().to(device)
    data_path = f"../input/validate/validate/{dataset_name}"
    data_loader = get_data(256, batch_size=num_images, data_dir=data_path, lab=False)
    img_real_rgb, _ = next(iter(data_loader))
    n = len(net_names)
    fig = plt.figure(figsize=(4*num_images, 4*(n+1)))
    with torch.no_grad():
        for i, net_name in enumerate(net_names):
            G_path = f"../input/all-checkpoints/generator_{net_name}.pth"
            G.load_state_dict(torch.load(G_path))
            G.eval()
            img_real_lab = rgb_to_lab(img_real_rgb).to(device)
            img_bw = img_real_lab[:,0,:,:].unsqueeze(1)
            img_fake_lab = torch.cat([img_bw, G(img_bw)], 1)
            img_fake_rgb = lab_to_rgb(img_fake_lab)

            print(f"Generator {net_name} results")

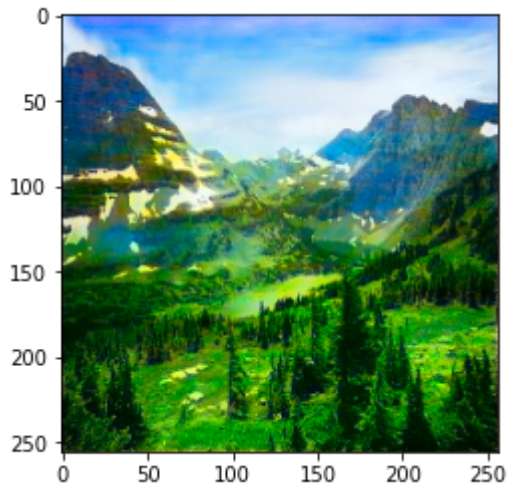
            for j in range(num_images):
                fig.add_subplot(n+1, num_images, 1 + num_images*i + j)
                plt.axis('off')
                plt.imshow(img_fake_rgb[j].cpu().permute(1,2,0))

            for j in range(num_images):
                fig.add_subplot(n+1, num_images, num_images*n + 1 + j)
                plt.axis('off')
                plt.imshow(img_real_rgb[j].cpu().permute(1,2,0))
    plt.show()

def color_imgs(img, G):
    G.eval()
    img_real_lab = rgb_to_lab(img).to(device)
    img_bw = img_real_lab[:,0,:,:].unsqueeze(1)
    img_fake_lab = torch.cat([img_bw, G(img_bw)], 1)
    img_fake_rgb = lab_to_rgb(img_fake_lab)
    return img_fake_rgb.detach()
```

```
net_name = "290_v2_aug_3"
G = TheGenerator().to(device)
G.load_state_dict(torch.load(f"../input/all-checkpoints/generator_{net_name}.pth"))
img = get_img("../input/luululu/glacier.jpg", lab=False)[None]
plt.imshow(color_imgs(img,G)[0].cpu().permute(1,2,0))
```

<matplotlib.image.AxesImage at 0x7fd29ae24c90>



▼ pretty images

```
# net_names = ['50', '90', '100_aug', '160_aug_2', '200_aug_3', '250_v2_aug_3', '250_v2_aug_3_vg']
net_names = ['50', '200_aug_3', '290_v2_aug_3']
show_results(net_names, 'mountain', 8)
```

Generator 50 results
Generator 200_aug_3 results
Generator 290_v2_aug_3 results

