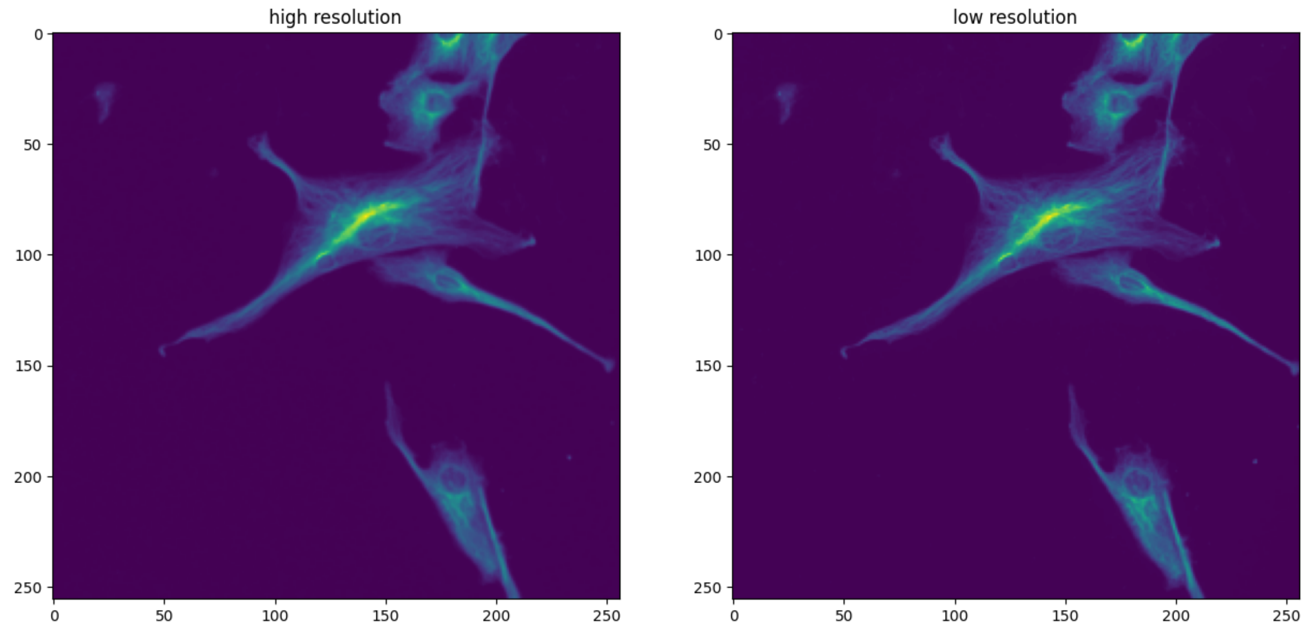
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import os
from PIL import Image
from tqdm import tqdm
import random
import time
import copy
import itertools
import shutil
from sklearn.model_selection import train_test_split

import torchvision
from torchvision import transforms, models
from torchvision.transforms import ToTensor, Normalize, ToPILImage
from torchvision.transforms.functional import hflip, vflip, rotate, adjust_hue
import cv2
from skimage import io, transform
from skimage import io, transform
import albumentations as A
from albumentations import (HorizontalFlip, ShiftScaleRotate, Normalize, Resize, Compose, 

import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import torch.backends.cudnn as cudnn
from torchvision.models.feature_extraction import create_feature_extractor
from torchsummary import summary

cudnn.benchmark = True


# Key Parameters
download_original= 0 # download the slide image and masks from google bucket
BATCH_SIZE = 2

# original width and height of image (standardized in all images)
width, height = 256, 256


# download the image the google bucket that I set up
# credit: http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html
if download_original == 1:
    image_url = 'https://storage.googleapis.com/acv_project/floro_train.zip'
    !curl -O $image_url
    !unzip floro_train -d fluo
    !rm floro_train.zip
    image_url = 'https://storage.googleapis.com/acv_project/floro_test.zip'
    !curl -O $image_url
    !unzip floro_test -d fluo
    !rm floro_test.zip


class FluoroDataset(torch.utils.data.Dataset):
    def __init__(self, img_dir, transforms = None):
        self.transforms = Compose([A.RandomRotate90(p=0.5), A.HorizontalFlip(p=0.5), A.Ver
```

```
        # corresponding files have the same file names
        self.file_HR_dir = img_dir + '/target'
        self.file_HR = os.listdir(img_dir + '/target')
        self.file_SR_dir = img_dir + '/input'

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

    def __getitem__(self,idx):
        try:

            # read images and masks from directory.
            # Masks represent high-resolution images (targets) for low-res images.
            img = io.imread(os.path.join(self.file_SR_dir, self.file_HR[idx])).astype('flo
            size = 256
            img = transform.resize(img,(size,size))
            img = cv2.normalize(img, None, 0, 1.0, cv2.NORM_MINMAX, dtype=cv2.CV_32F)

            mask = io.imread(os.path.join(self.file_HR_dir, self.file_HR[idx])).astype('fl
            mask = transform.resize(mask,(size,size))
            mask = cv2.normalize(mask, None, 0, 1.0, cv2.NORM_MINMAX, dtype=cv2.CV_32F)

            augmented = self.transforms(image=img, mask=mask) # data augmentation
            img = augmented['image']
            mask = augmented['mask']

            # convert everything into a torch.Tensor
            mask = torch.as_tensor(mask, dtype=torch.float32)
            img = torch.as_tensor(img, dtype=torch.float32)

            img = img.unsqueeze(0)
            mask = mask.unsqueeze(0)

            return {"file_name": self.file_HR[idx], "img": img, "mask": mask}

        except Exception as exc:
            return None

def collate_fn(batch):
    # Filter failed images first
    batch = list(filter(lambda x: x is not None, batch))

    # Now collate into mini-batches
    img = torch.stack([b["img"] for b in batch])
    mask = torch.stack([b["mask"] for b in batch])
    return mask, img

image_datasets = {x: FluoroDataset(os.path.join('./fluo', x)) for x in ['train', 'test']}
# implement custom image_dataset and wrap it with the dataloader
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=BATCH_SIZE, dr
                                              shuffle=True, num_workers=0, collate_fn = co
               for x in ['train', 'test']}
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'test']}
print('size of dataset', dataset_sizes)
```

```
size of dataset {'train': 48, 'test': 5}
```

```
# sample output
sample = next(iter(dataloaders['train']))
```

```
lr = sample[0][0]
sr = sample[1][0]
fig, axs = plt.subplots(1, 2, figsize=(15, 10))

# Display the LR and HR images using matplotlib
axs[0].imshow(ToPILImage()(sr))
axs[0].set_title('high resolution')
axs[1].imshow(ToPILImage()(lr))
axs[1].set_title('low resolution')
plt.show()
```




```
# SRGAN Generator
# adapted from https://github.com/Lornatang/SRGAN-PyTorch/blob/main/model.py

def ResidualConvBlock(channels):
    return nn.Sequential(nn.Conv2d(in_channels = channels,
                                   out_channels = channels,
                                   kernel_size = (3, 3),
                                   stride = (1, 1),
                                   padding = (1, 1),
                                   bias=False),
                         nn.BatchNorm2d(channels),
                         nn.PReLU(), # great for mapping low-resolution images to high-res
                         nn.Conv2d(channels, channels, (3, 3), (1, 1), (1, 1), bias=False)
                         nn.BatchNorm2d(channels),
                         nn.Dropout(p=0.05))

# only zoom in by 2x each time
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()

        in_channels = 1
        out_channels = 1
        channels = 64 # this is the intermediate channels in the network

        # low frequency information extraction layer
        self.conv1 = nn.Sequential(
```

```
            nn.Conv2d(in_channels, channels, (9, 9), (1, 1), (4, 4)),
            nn.PReLU())

        # 5 Residual Blocks (note that there will be an element wise sum)
        self.rcb1 = ResidualConvBlock(channels)
        self.rcb2 = ResidualConvBlock(channels)
        self.rcb3 = ResidualConvBlock(channels) # reduced to prevent overfitting


        # high-frequency information linear fusion layer
        self.conv2 = nn.Sequential(nn.Conv2d(in_channels = channels,
                                             out_channels = channels,
                                             kernel_size = (3, 3),
                                             stride = (1, 1),
                                             padding = (1, 1),
                                             bias=False),
                                   nn.BatchNorm2d(channels))

        # zoom block (we will only be zooming up by factor 2 each time)
        self.ub1 = nn.Sequential(nn.Conv2d(in_channels = channels,
                                          out_channels = channels * 4,
                                          kernel_size = (3, 3),
                                          stride = (1, 1),
                                          padding = (1, 1)),
                                nn.PixelShuffle(2),
                                nn.PReLU(),
                                nn.AvgPool2d(2)) # note the addition of the average poolin
        self.ub2 = nn.Sequential(nn.Conv2d(in_channels = channels,
                                          out_channels = channels * 4,
                                          kernel_size = (3, 3),
                                          stride = (1, 1),
                                          padding = (1, 1)),
                                nn.PixelShuffle(2),
                                nn.PReLU(),
                                nn.AvgPool2d(2)) # note the addition of the average poolin

        # reconstruction block
        self.conv3 = nn.Conv2d(in_channels = channels,
                               out_channels = out_channels,
                               kernel_size = (9, 9),
                               stride = (1, 1),
                               padding = (4, 4)) # retains the dimension of the output

    def forward(self, x):
        out1 = self.conv1(x)
        rcb1 = self.rcb1(out1)
        rcb2 = self.rcb2(torch.add(out1, rcb1)) # included the skip connections
        out2 = self.rcb3(torch.add(rcb1, rcb2))
        out2 = self.conv2(out2)
        out = torch.add(out1, out2)
        out = self.ub1(out)
        out = self.ub2(out)
        out = self.conv3(out)
        return out

# unit test
generator = Generator()
img = next(iter(dataloaders['train']))
lr = img[0]
gen_sr = generator(lr)[0]
```

```
sr = img[1]

output = generator(lr)
print(output.shape)
```

```
     torch.Size([2, 1, 256, 256])
```

```
def DiscriminatorConvBlock(in_channels, out_channels):
    return nn.Sequential(nn.Conv2d(in_channels = in_channels,
                                   out_channels = in_channels,
                                   kernel_size = (3, 3),
                                   stride = (2, 2),
                                   padding = (1, 1),
                                   bias=False),
                         nn.BatchNorm2d(in_channels),
                         nn.LeakyReLU(0.2, True),
                         nn.Conv2d(in_channels = in_channels,
                                   out_channels = out_channels,
                                   kernel_size = (3, 3),
                                   stride = (2, 2),
                                   padding = (1, 1),
                                   bias=False),
                         nn.BatchNorm2d(out_channels),
                         nn.LeakyReLU(0.2, True),
                         nn.Dropout(p=0.05))

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        # input shape (2) x 256 x 256
        self.conv1 = nn.Sequential(nn.Conv2d(2, 64, (3, 3), (1, 1), (1, 1), bias=True),
                                   nn.LeakyReLU(0.2, True))
        self.conv2 = DiscriminatorConvBlock(64, 128)
        self.conv3 = DiscriminatorConvBlock(128, 256)
        self.conv4 = DiscriminatorConvBlock(256, 512)
        self.conv5 = DiscriminatorConvBlock(512, 1024)
        # input shape (1024) * 1 * 1
        self.classifier = nn.Sequential(nn.Linear(1024, 1024),
                                        nn.LeakyReLU(0.2, True),
                                        nn.Dropout(p=0.05),
                                        nn.Linear(1024, 1),
                                        nn.Sigmoid()) # for BCE loss

    def forward(self, lr, sr):
        x = torch.cat((lr, sr), 1) # need both the input and the output to distinguish
        out = self.conv1(x)
        out = self.conv2(out)
        out = self.conv3(out)
        out = self.conv4(out)
        out = self.conv5(out)
        out = torch.flatten(out, 1)
        out = self.classifier(out)
        return out

# unit test
discriminator = Discriminator()
img = next(iter(dataloaders['train']))
lr = img[0]
gen_sr = generator(lr)[0]
```

```
sr = img[1]
output = discriminator(lr, sr)
print(output.shape)

    torch.Size([2, 1])


# reference: https://towardsdatascience.com/light-on-math-machine-learning-intuitive-guide
# content loss (loss based on the perceptual quality of the generated SR image as compared
class ContentLoss(nn.Module):
    def __init__(self):
        super(ContentLoss, self).__init__()

        # load the VGG19 model trained on the ImageNet dataset
        # vgg: features (36 nodes) -> avg pool -> classifier

        model = models.vgg19(weights=models.VGG19_Weights.IMAGENET1K_V1)

        # standard basic (this is hardcoded to prevent modifications)
        self.feature_model_extractor_node = "features.35" # extract the thirty-sixth layer

        # feature extractor
        self.feature_extractor = create_feature_extractor(model, [self.feature_model_extra

        # set to validation mode
        self.feature_extractor.eval()

        # Freeze model parameters.
        for model_parameters in self.feature_extractor.parameters():
            model_parameters.requires_grad = False

        self.mse_loss = nn.MSELoss()

    def forward(self, out_image, target_image):
        # put feature extractor to the same device
        if out_image.is_cuda:
            self.feature_extractor.cuda()
        # standardized operations
        out_feature = self.feature_extractor(out_image)[self.feature_model_extractor_node]
        target_feature = self.feature_extractor(target_image)[self.feature_model_extractor_
        # find the feature map mse between the two images
        loss = self.mse_loss(target_feature, out_feature)
        return loss

# reference: https://towardsdatascience.com/super-resolution-a-basic-study-e01af1449e13
# total variation loss (supress the noise in the generated image)
class TVLoss(nn.Module):
    def __init__(self):
        super(TVLoss, self).__init__()

    def forward(self, x):
        batch_size = BATCH_SIZE
        h_x = height
        w_x = width
        h_tv = torch.pow((x[:, :, 1:, :] - x[:, :, :h_x - 1, :]), 2).sum()
        w_tv = torch.pow((x[:, :, :, 1:] - x[:, :, :, :w_x - 1]), 2).sum()
        return (h_tv + w_tv)/(w_x * h_x * 3 * batch_size)

# generator loss
# reference: https://github.com/leftthomas/SRGAN
```

```
class GeneratorLoss(nn.Module):
    def __init__(self):
        super(GeneratorLoss, self).__init__()
        # Load the VGG19 model trained on the ImageNet dataset.
        self.content_loss = ContentLoss()
        self.tv_loss = TVLoss()
        self.pixel_loss = nn.MSELoss()

    def forward(self, out_labels, out_images, target_images):
        adversarial_loss = torch.mean(1 - out_labels)
        content_loss = self.content_loss(torch.cat((out_images, out_images, out_images), 1
                                         torch.cat((target_images, target_images, target_i
        tv_loss = self.tv_loss(out_images)
        pixel_loss = self.pixel_loss(out_images, target_images)
        # print('adversarial_loss', adversarial_loss)
        # print('content loss:', content_loss)
        # print('total variation loss:', tv_loss)
        # print('pixel_loss:', pixel_loss)

        return 0.01 * adversarial_loss + content_loss +  tv_loss + pixel_loss

# unit test
img = next(iter(dataloaders['train']))
sr1 = img[1]
img = next(iter(dataloaders['train']))
sr2 = img[1]
gl = GeneratorLoss()
print('generator loss:', gl(torch.ones(BATCH_SIZE), sr1, sr2))
```

```
generator loss: tensor(0.0920)
```

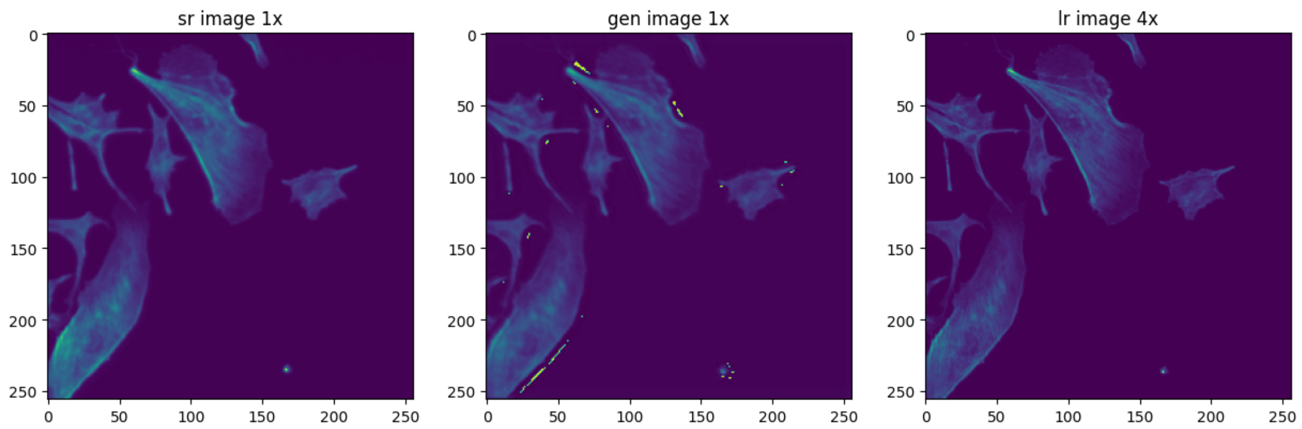
```
# model training
# create a place to save memory
model_path = './model'
if not os.path.exists(model_path):
    os.mkdir(model_path) # save all models to this path


# train generator network first (warm start)

# parameters for training the generator network (round 1)
device = 'cuda:0'
model_g = Generator().to(device)
optimizer_g = optim.Adam(model_g.parameters(), lr=0.001)
scheduler_g = lr_scheduler.StepLR(optimizer_g, step_size = 8, gamma = 0.5)
criterion_g = GeneratorLoss()
num_epochs = 10 # we just want to warm start the generator here


# train the generator Model
train_loss_list = []
val_loss_list = []
best_loss = 100.0

for epoch in range(num_epochs):
    # training step
    model_g.train()
    torch.set_grad_enabled(True)
    train_running_loss = 0
```

```
    for lr, sr in tqdm(dataloaders['train']):
        lr = lr.to(device)
        sr = sr.to(device)
        optimizer_g.zero_grad()
        outputs = model_g(lr)
        loss = criterion_g(torch.ones(output.shape, device = device), outputs, sr) # adver
        loss.backward()
        optimizer_g.step()
        train_running_loss += loss.item()
    scheduler_g.step()
    train_loss = train_running_loss * BATCH_SIZE/dataset_sizes['train']
    train_loss_list.append(train_loss)

    # validation step
    model_g.eval()
    torch.set_grad_enabled(False)
    # visualize how the mask prediction changes over time

    val_running_loss = 0
    for lr, sr in dataloaders['test']:
        lr = lr.to(device)
        sr = sr.to(device)
        outputs = model_g(lr)
        loss = criterion_g(torch.ones(output.shape, device = device), outputs, sr) # adver
        val_running_loss += loss.item()
    val_loss = val_running_loss * BATCH_SIZE/dataset_sizes['test']
    val_loss_list.append(val_loss)

    # update the best model
    if val_loss < best_loss:
        best_loss = val_loss
        torch.save(model_g.state_dict(), './model/generator')

    print(f'epoch: {epoch + 1}/{num_epochs}, Train Loss: {train_loss:.8f}, Test Loss: {val
```

```
100%|██████████| 24/24 [00:15<00:00,  1.57it/s]
epoch: 1/10, Train Loss: 0.07713818, Test Loss: 0.05645990
100%|██████████| 24/24 [00:11<00:00,  2.08it/s]
epoch: 2/10, Train Loss: 0.03909090, Test Loss: 0.03961768
100%|██████████| 24/24 [00:11<00:00,  2.02it/s]
epoch: 3/10, Train Loss: 0.03535770, Test Loss: 0.01210627
100%|██████████| 24/24 [00:11<00:00,  2.08it/s]
epoch: 4/10, Train Loss: 0.02779945, Test Loss: 0.02373375
100%|██████████| 24/24 [00:11<00:00,  2.11it/s]
epoch: 5/10, Train Loss: 0.02729281, Test Loss: 0.01823043
100%|██████████| 24/24 [00:11<00:00,  2.08it/s]
epoch: 6/10, Train Loss: 0.02469430, Test Loss: 0.01906823
100%|██████████| 24/24 [00:11<00:00,  2.09it/s]
epoch: 7/10, Train Loss: 0.03198801, Test Loss: 0.02263202
100%|██████████| 24/24 [00:11<00:00,  2.10it/s]
epoch: 8/10, Train Loss: 0.02675646, Test Loss: 0.01650772
100%|██████████| 24/24 [00:11<00:00,  2.11it/s]
epoch: 9/10, Train Loss: 0.01978577, Test Loss: 0.01129886
100%|██████████| 24/24 [00:11<00:00,  2.11it/s]
epoch: 10/10, Train Loss: 0.01906228, Test Loss: 0.01411813
```

```
# unit test
# sample output from pretrained generator
model_g.to('cpu')
img = next(iter(dataloaders['test']))
lr = img[0]
```

```
    gen_sr = model_g(lr)[0]
    lr = lr[0]
    sr = img[1][0]

    fig, axs = plt.subplots(1, 3, figsize=(15, 10))

    # Display the LR and HR images using matplotlib
    axs[0].imshow(ToPILImage()(sr))
    axs[0].set_title('sr·image·1x')
    axs[1].imshow(ToPILImage()(gen_sr))
    axs[1].set_title('gen·image·1x')
    axs[2].imshow(ToPILImage()(lr))
    axs[2].set_title('lr·image·4x')
    plt.show()
```




```
# parameters for training the discriminator network
model_g.load_state_dict(torch.load('./model/generator'))
model_g.to(device)
model_d = Discriminator().to(device)
optimizer_d = optim.Adam(model_d.parameters(), lr=0.01)
criterion_d = nn.BCELoss()
num_epochs = 5 # warm start so does not need that many


# warm start the discriminator model (4x -> 1x)
# note that we are simplifying the loss function for the discriminator
discriminator_loss_list = []
discriminator_val_loss_list = []
best_loss = 100.0

for epoch in range(num_epochs):
    # train step
    running_loss_d = 0
    running_loss_g = 0
    model_d.train()
    model_g.train()
    torch.set_grad_enabled(True)
    for lr, sr in tqdm(dataloaders['train']):
        lr = lr.to(device)
        sr = sr.to(device)
        # log(D(x))
        optimizer_d.zero_grad()
        output = model_d(lr, sr)
        loss_d_real = criterion_d(output, torch.ones(output.shape, device = device))
        loss_d_real.backward()
```

```
            # log(1 - D(G(z)))
            fake_sr = model_g(lr)
            output = model_d(lr, fake_sr)
            loss_d_fake = criterion_d(output, torch.zeros(output.shape, device = device))
            loss_d_fake.backward(retain_graph=True)
            loss_d = loss_d_real + loss_d_fake
            optimizer_d.step()
            running_loss_d += loss_d.item()
        discriminator_loss = running_loss_d/dataset_sizes['train']
        discriminator_loss_list.append(discriminator_loss)

        # validation step
        model_d.eval()
        val_running_loss_d = 0
        torch.set_grad_enabled(False)
        for lr, sr in dataloaders['test']:
            lr = lr.to(device)
            sr = sr.to(device)
            # log(D(x))
            output = model_d(lr, sr)
            loss_d_real = criterion_d(output, torch.ones(output.shape, device = device))
            # log(1 - D(G(z)))
            fake_sr = model_g(lr)
            output = model_d(lr, fake_sr)
            loss_d_fake = criterion_d(output, torch.zeros(output.shape, device = device))
            loss_d = loss_d_real + loss_d_fake
            val_running_loss_d += loss_d.item()
        val_loss = val_running_loss_d/dataset_sizes['test']
        discriminator_val_loss_list.append(val_loss)
        # update the best model
        if val_loss < best_loss:
            # save the weights
            best_loss = val_loss
            torch.save(model_d.state_dict(), './model/discriminator')
        # print the progress to determine if the progress has stagnated
        print(f'epoch: {epoch+1}/{num_epochs}, Discriminator Loss: {discriminator_loss:.4f}, D
```

```
100%|██████████| 24/24 [00:12<00:00,  1.90it/s]
epoch: 1/5, Discriminator Loss: 2.3554, Discriminator Validation Loss: 6.95406504
100%|██████████| 24/24 [00:11<00:00,  2.15it/s]
epoch: 2/5, Discriminator Loss: 1.4032, Discriminator Validation Loss: 1.42550383
100%|██████████| 24/24 [00:11<00:00,  2.11it/s]
epoch: 3/5, Discriminator Loss: 1.2189, Discriminator Validation Loss: 1.03043013
100%|██████████| 24/24 [00:11<00:00,  2.13it/s]
epoch: 4/5, Discriminator Loss: 0.9331, Discriminator Validation Loss: 0.69658544
100%|██████████| 24/24 [00:11<00:00,  2.12it/s]
epoch: 5/5, Discriminator Loss: 0.7951, Discriminator Validation Loss: 0.91089859
```

```
# load the pretrained generator and discriminator
model_g.load_state_dict(torch.load('./model/generator'))
model_g.to(device)
model_d.load_state_dict(torch.load('./model/discriminator'))
model_d.to(device)

# set the number of epochs
num_epochs = 50

# train the SRGAN model (4x -> 1x)
discriminator_loss_list = []
generator_loss_list = []
```

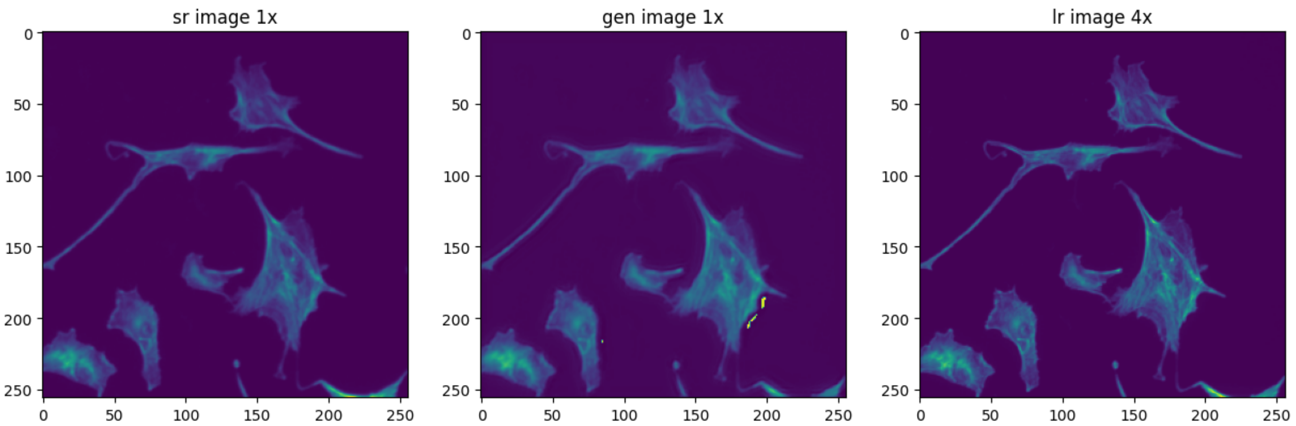
```
    generator_val_loss_list = []
    best_loss = 100.0

    for epoch in range(num_epochs):
        # train step
        running_loss_d = 0
        running_loss_g = 0
        model_d.train()
        model_g.train()
        torch.set_grad_enabled(True)
        for lr, sr in tqdm(dataloaders['train']):
            lr = lr.to(device)
            sr = sr.to(device)
            ############################
            # (1) update D network: maximize log(D(x))+log(1-D(G(z)))
            ###########################
            optimizer_d.zero_grad()
            output = model_d(lr, sr)
            loss_d_real = criterion_d(output, torch.ones(output.shape, device = device))
            loss_d_real.backward()
            # log(1 - D(G(z)))
            fake_sr = model_g(lr)
            output = model_d(lr, fake_sr)
            loss_d_fake = criterion_d(output, torch.zeros(output.shape, device = device))
            loss_d_fake.backward(retain_graph=True)
            loss_d = loss_d_real + loss_d_fake
            optimizer_d.step()
            running_loss_d += loss_d.item()
            ############################
            # (2) update G network: minimize 1-D(G(z)) + Content Loss + TV Loss
            ###########################
            optimizer_g.zero_grad()
            # note that fake labels are real for generator cost
            loss_g = criterion_g(out_labels = output, out_images = fake_sr, target_images = sr)
            loss_g.backward()
            optimizer_g.step()
            running_loss_g += loss_g.item()
        discriminator_loss = running_loss_d/dataset_sizes['train']
        discriminator_loss_list.append(discriminator_loss)
        generator_loss = running_loss_g/dataset_sizes['train']
        generator_loss_list.append(generator_loss)

        # validation step
        model_g.eval()
        val_running_loss = 0
        torch.set_grad_enabled(False)
        for lr, sr in dataloaders['test']:
            lr = lr.to(device)
            sr = sr.to(device)
            fake_sr = model_g(lr)
            output = model_d(lr, fake_sr)
            loss = criterion_g(out_labels = output, out_images = fake_sr, target_images = sr)
            val_running_loss += loss.item()
        val_loss = val_running_loss/dataset_sizes['test']
        generator_val_loss_list.append(val_loss)
        # update the best model
        if val_loss < best_loss:
            # save the weights
            best_loss = val_loss
            torch.save(model_g.state_dict(), './model/gan_generator')
            torch.save(model_d.state_dict(), './model/gan_discriminator')
```

```
    torch.save(model_d.state_dict(), './model/gan_discriminator')

    # print the progress to determine if the progress has stagnated
    print(f'epoch: {epoch+1}/{num_epochs}, Generator Loss: {generator_loss:.4f}, Discrimina
```

```
 100%|██████████| 24/24 [00:12<00:00,  1.96it/s]
 epoch: 1/50, Generator Loss: 0.0120, Discriminator Loss: 0.7506, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.96it/s]
 epoch: 2/50, Generator Loss: 0.0132, Discriminator Loss: 0.7708, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.96it/s]
 epoch: 3/50, Generator Loss: 0.0125, Discriminator Loss: 0.7648, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.96it/s]
 epoch: 4/50, Generator Loss: 0.0113, Discriminator Loss: 0.7822, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 5/50, Generator Loss: 0.0102, Discriminator Loss: 0.7671, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 6/50, Generator Loss: 0.0105, Discriminator Loss: 0.7566, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.89it/s]
 epoch: 7/50, Generator Loss: 0.0130, Discriminator Loss: 0.7850, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 8/50, Generator Loss: 0.0110, Discriminator Loss: 0.9987, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.95it/s]
 epoch: 9/50, Generator Loss: 0.0110, Discriminator Loss: 0.9036, Generator Validation
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 10/50, Generator Loss: 0.0109, Discriminator Loss: 0.7788, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.95it/s]
 epoch: 11/50, Generator Loss: 0.0104, Discriminator Loss: 0.7679, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.95it/s]
 epoch: 12/50, Generator Loss: 0.0122, Discriminator Loss: 0.7981, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.97it/s]
 epoch: 13/50, Generator Loss: 0.0106, Discriminator Loss: 0.7609, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.95it/s]
 epoch: 14/50, Generator Loss: 0.0106, Discriminator Loss: 0.7666, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 15/50, Generator Loss: 0.0121, Discriminator Loss: 0.8051, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 16/50, Generator Loss: 0.0101, Discriminator Loss: 0.7521, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.92it/s]
 epoch: 17/50, Generator Loss: 0.0103, Discriminator Loss: 0.7746, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 18/50, Generator Loss: 0.0115, Discriminator Loss: 0.7231, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 19/50, Generator Loss: 0.0102, Discriminator Loss: 0.8841, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 20/50, Generator Loss: 0.0101, Discriminator Loss: 0.7334, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 21/50, Generator Loss: 0.0100, Discriminator Loss: 0.7168, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.93it/s]
 epoch: 22/50, Generator Loss: 0.0095, Discriminator Loss: 0.7123, Generator Validatio
 100%|██████████| 24/24 [00:13<00:00,  1.85it/s]
 epoch: 23/50, Generator Loss: 0.0097, Discriminator Loss: 0.7075, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.95it/s]
 epoch: 24/50, Generator Loss: 0.0099, Discriminator Loss: 0.7591, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 25/50, Generator Loss: 0.0088, Discriminator Loss: 0.7702, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.89it/s]
 epoch: 26/50, Generator Loss: 0.0090, Discriminator Loss: 0.7402, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.89it/s]
 epoch: 27/50, Generator Loss: 0.0096, Discriminator Loss: 0.7095, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.92it/s]
 epoch: 28/50, Generator Loss: 0.0088, Discriminator Loss: 0.7267, Generator Validatio
 100%|██████████| 24/24 [00:12<00:00,  1.94it/s]
 epoch: 29/50, Generator Loss: 0.0083, Discriminator Loss: 0.7480, Generator Validatio
```

```
# unit test
# sample output from pretrained generator
```

```
# sample output from pretrained generator
model_g.to('cpu')
img = next(iter(dataloaders['test']))
lr = img[0]
gen_sr = model_g(lr)[0]
lr = lr[0]
sr = img[1][0]

fig, axs = plt.subplots(1, 3, figsize=(15, 10))

# Display the LR and HR images using matplotlib
axs[0].imshow(ToPILImage()(sr))
axs[0].set_title('sr image 1x')
axs[1].imshow(ToPILImage()(gen_sr))
axs[1].set_title('gen image 1x')
axs[2].imshow(ToPILImage()(lr))
axs[2].set_title('lr image 4x')
plt.show()
```




```
# adapted from xingyue model

# !pip install torchmetrics
# !pip install lpips
from torchmetrics import PeakSignalNoiseRatio
from torchmetrics import StructuralSimilarityIndexMeasure
import lpips
psnr = PeakSignalNoiseRatio().to(device)
ssim = StructuralSimilarityIndexMeasure(data_range=1.0).to(device)
loss_fn = lpips.LPIPS(net='alex').to(device)

# Evaluate model performance on test dataset (modified from xinyue model)
l1_loss = []
mse_loss = []
psnr_list = []
ssim_list = []
output_list = []
lpips_list = []
criterion1 = nn.L1Loss()
criterion2 = nn.MSELoss()
model_g.to(device)
model_g.eval()
with torch.no_grad():
    for lr, sr in dataloaders['test']:
        lr = lr.to(device)
        sr = sr.to(device)
```

```
        fake_sr = model_g(lr)
        # Compute L1 loss
        loss = criterion1(fake_sr, sr)
        l1_loss.append(loss.item())

        # Compute MSE loss
        loss2 = criterion2(fake_sr, sr)
        mse_loss.append(loss2.item())

        # Compute PSNR
        psnr_value = psnr(fake_sr, sr)
        psnr_value = psnr_value.clone().cpu().detach().numpy()
        psnr_list.append(psnr_value)

        # Compute SSIM
        ssim_value = ssim(fake_sr, sr)
        ssim_value = ssim_value.clone().cpu().detach().numpy()
        ssim_list.append(ssim_value)

        # Compute LPIPS
        d = loss_fn.forward(fake_sr, sr).clone().cpu().detach().numpy()
        lpips_list.append(d)

print('l1_loss:', np.mean(l1_loss))
print('mse_loss', np.mean(mse_loss))
print('psnr:', np.mean(psnr_list))
print('lpips:', np.mean(lpips_list))
print('ssim:', np.mean(ssim_list))
```

```
Setting up [LPIPS] perceptual loss: trunk [alex], v[0.1], spatial [off]
/usr/local/lib/python3.9/dist-packages/torchvision/models/_utils.py:208: UserWarning:
  warnings.warn(
/usr/local/lib/python3.9/dist-packages/torchvision/models/_utils.py:223: UserWarning:
  warnings.warn(msg)
Loading model from: /usr/local/lib/python3.9/dist-packages/lpips/weights/v0.1/alex.pt
l1_loss: 0.04129911307245493
mse_loss 0.004712474066764116
psnr: 25.471146
lpips: 0.052593455
ssim: 0.60087717
```


✓ 2s completed at 4:07 PM