Super_Resolution_GANs_problem

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The goal of this homework is to super-resolve a very low resolution image (32x32) to a high resolution image (1024x1024) using a trained image prior as discussed in class. The generative prior used here is a style GAN, its code is already provided, and its trained parameters can be downloaded from: https://drive.google.com/uc?id=1TCViX1YpQyRsklTVYEJwdbmK91vklCo8

We start by loading the provided high resolution image, then downscaling it by a factor of 32. We then recover the original high resolution image by minimizing equation 3 in the lecture notes using gradient descent.

[32]:
```
from google.colab import drive
import os

gdrive_path = '/content/gdrive/MyDrive/Colab Notebooks/dlip/HW8/'

# This will mount your google drive under 'MyDrive'
drive.mount('/content/gdrive', force_remount=True)
# In order to access the files in this notebook we have to navigate to the␣
↪correct folder
os.chdir(gdrive_path)
# Check manually if all files are present
print(sorted(os.listdir()))
```

```
Mounted at /content/gdrive
['.DS_Store', 'Super_Resolution_GANs_problem.ipynb', '__MACOSX', '__pycache__',
'bicubic.py', 'colab_pdf.py', 'gaussian_fit.pt', 'gt.jpeg', 'stylegan.py',
'synthesis.pt']
```

[2]:
```
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
from tqdm.notebook import tqdm

import torch
import torchvision
```

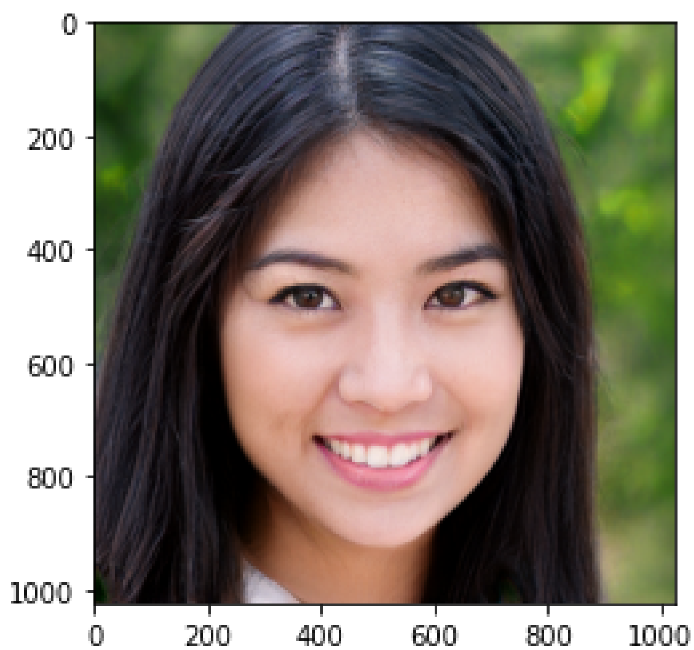
```python
from bicubic import BicubicDownSample  #Downscaler
from stylegan import G_synthesis       #style GAN
```

[3]:
```python
gt = Image.open(gdrive_path + 'gt.jpeg') #load ground truth high resolution img
gt = torchvision.transforms.ToTensor()(gt)
gt = gt.unsqueeze(0)

print(gt.shape)
plt.imshow(gt.squeeze(0).permute(1,2,0))
```

```
torch.Size([1, 3, 1024, 1024])
```

[3]:
```
<matplotlib.image.AxesImage at 0x7ff55634a210>
```



[4]:
```python
device = 'cuda'
gt = gt.to(device)
```

[5]:
```python
#Downscaling
A = BicubicDownSample(factor=32)
y = A(gt)
y = y.clamp(0,1)

print(y.shape)
plt.imshow(y.cpu().squeeze(0).permute(1,2,0))
```

```
torch.Size([1, 3, 32, 32])
```

[5]:
```
<matplotlib.image.AxesImage at 0x7ff54d3e4c90>
```

[6]:
```python
#Load trained style GAN
model = G_synthesis().to(device)
state_dict = torch.load(gdrive_path + 'synthesis.pt')  #enter path to the downloaded state_dict
model.load_state_dict(state_dict)
```

[6]:
```
<All keys matched successfully>
```

[7]:
```python
#Scaling factors
gaussian_fit = torch.load(gdrive_path + "gaussian_fit.pt")
lrelu = torch.nn.LeakyReLU(negative_slope=0.2)
```

[8]:
```python
#Load noise input to GAN, note that z1 is trainable but z2 is kept fixed.

z1 = torch.randn((1, 18, 512), dtype=torch.float, requires_grad=True, device=device)

#Generate list of noise tensors
z2 = [] # stores all of the noise tensors

for i in range(18):
    # dimension of the ith noise tensor
```

```
    res = (1, 1, 2**(i//2+2), 2**(i//2+2))

    new_noise = torch.randn(res, dtype=torch.float, device=device)
    new_noise.requires_grad = False

    z2.append(new_noise)
```

[9]:
```
def mse(gt: torch.Tensor, pred:torch.Tensor)-> torch.Tensor:
    loss = torch.nn.MSELoss()
    return loss(gt,pred)

#Takes as input noise, and returns an image
def G(z1,z2):
    latent = lrelu(z1*gaussian_fit["std"] + gaussian_fit["mean"])
    img = model(latent, z2)
    img = (img + 1)/2
    img = img.clamp(0,1)
    return img
```

Write your code to recover the original image by optimizing over z_1

Criterion: $\min_{\mathbf{z}} \frac{1}{2}||\mathbf{A}G(\mathbf{z}) - \mathbf{y}||_2^2 + \gamma||\mathbf{z}||_2^2$

[11]:
```
def ridge_mse(gt, pred, w, weight_decay=1e-6):
    loss = mse(gt, pred)
    # print(w.shape)
    # print(type(w))
    w_flat = w.flatten()
    loss += weight_decay * torch.linalg.norm(w_flat) / w_flat.size()[0]
    return loss

def training_step(z1, z2, ground_truth, learning_rate=1, weight_decay=1e-6,␣
↪num_steps=10000):
    optimizer = torch.optim.SGD([z1], lr=learning_rate, momentum=0.9)
    scheduler = torch.optim.lr_scheduler.MultiStepLR(optimizer,␣
↪milestones=[4000,8000], gamma=0.1)
    losses = []

    with tqdm(range(num_steps)) as tepoch:
      for _ in tepoch:
          # zero the parameter gradients
          optimizer.zero_grad()

          # forward + backward + optimize
          output = G(z1, z2)
          # loss = mse(ground_truth, A(output))
          loss = ridge_mse(ground_truth, A(output), z1, weight_decay)
```

```
            loss.backward()
            optimizer.step()

            losses.append(loss.item())

            tepoch.set_postfix(loss=loss.item())

    return z1, output, losses

z1_opt, rec_img, mse_losses = training_step(z1, z2, y)
```

```
0%|          | 0/10000 [00:00<?, ?it/s]
```

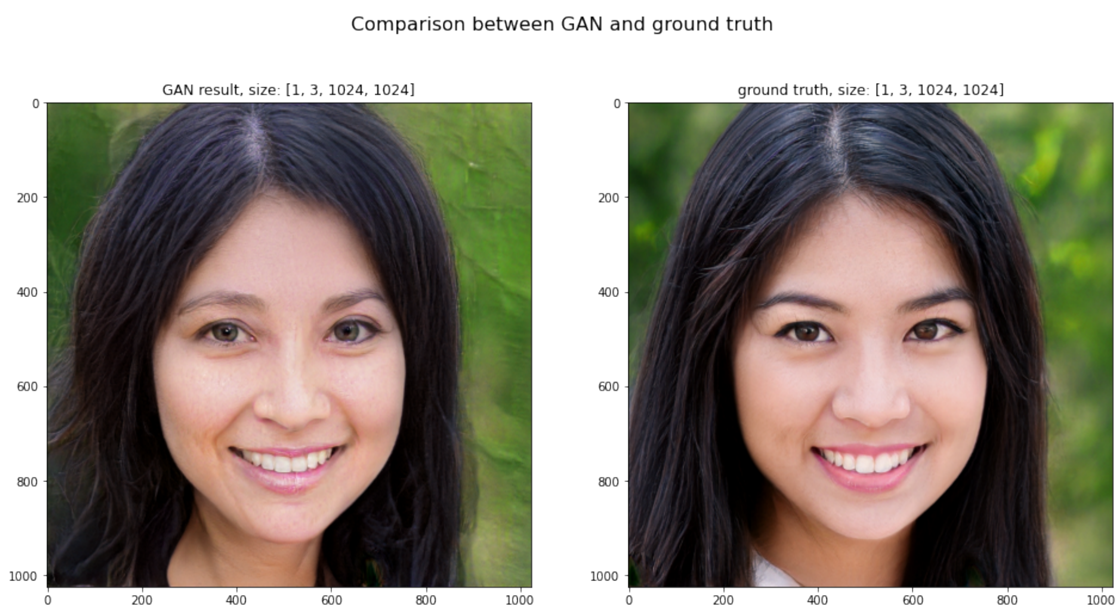
Plot your final image here

[15]:
```
fig, ax = plt.subplots(1, 2)
fig.set_figheight(8)
fig.set_figwidth(16)
fig.suptitle('Comparison between GAN and ground truth', fontsize=16)

ax[0].imshow(rec_img.cpu().detach().squeeze(0).permute(1,2,0))
ax[0].set_title('GAN result, size: '+ str(list(rec_img.size())))

ax[1].imshow(gt.cpu().squeeze(0).permute(1,2,0))
ax[1].set_title('ground truth, size: '+ str(list(gt.size())))
```

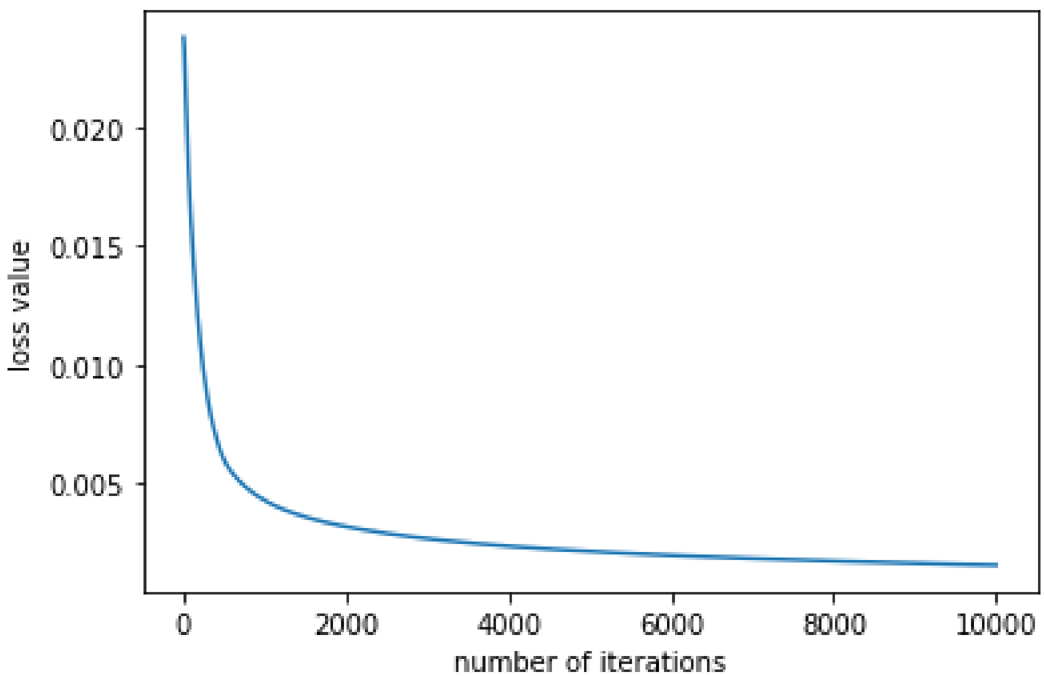
[15]:
```
Text(0.5, 1.0, 'ground truth, size: [1, 3, 1024, 1024]')
```



Print the MSE between your final image and the ground truth here

[18]:
```python
print('After %d iterations, the loss value = %f' % (len(mse_losses),
 mse_losses[-1]))
plt.plot(mse_losses)
plt.xlabel('number of iterations')
plt.ylabel('loss value')
plt.show()
```

```
After 10000 iterations, the loss value = 0.001585
```



0.0.1 Bonus

As we can see, the final image looks like a high resolution image of a face, but is not very similar to the ground truth. By additionally optimizing over z_2 as well, you can get slightly better results.

For achieving very good results, you can use the code from the following gihub repository: https://github.com/krantirk/Self-Supervised-photo