

Technological Institute of the Philippines
938 Aurora Blvd., Cubao, Quezon City

College of Engineering and Architecture
Electronics Engineering Department

Homework 2

NEURAL STYLE TRANSFER

Submitted by:
James Harold Palustre
ECE41S1

Submitted to:
Engr. Christian Lian Paulo Rioflorido, MSEE

October 2022

Neural style transfer is an application of Neural Networks where a style of an image is transferred to another. In this task, we used neural style transfer in transferring the art style of a certain painter into a subject image. I used in this assignment is the style of Pablo Picasso, a cubist painter, and our very own Fernando Amorsolo, a genre painter. I also used the VGG19 Architecture to this model.

First, import the libraries to be used in order for the program to work.

```
# import resources
%matplotlib inline

from PIL import Image
import matplotlib.pyplot as plt
import numpy as np

import torch
import torch.optim as optim
from torchvision import transforms, models
```

Now, we get the 'features' portion of the VGG19 because we will not be needing the 'classifier' portion.

```
vgg = models.vgg19(pretrained=True).features

for param in vgg.parameters():
    param.requires_grad_(False)
```

We now create a code that will run the program using GPU whenever it is available, and use CPU if there is none. We will also load the model to the device.

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

vgg.to(device)
```

```
Sequential(
  (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (1): ReLU(inplace=True)
  (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (3): ReLU(inplace=True)
  (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (6): ReLU(inplace=True)
  (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (8): ReLU(inplace=True)
  (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (11): ReLU(inplace=True)
  (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (13): ReLU(inplace=True)
  (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (15): ReLU(inplace=True)
  (16): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (17): ReLU(inplace=True)
  (18): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
```

```

(19): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(20): ReLU(inplace=True)
(21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(22): ReLU(inplace=True)
(23): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(24): ReLU(inplace=True)
(25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(26): ReLU(inplace=True)
(27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(29): ReLU(inplace=True)
(30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(31): ReLU(inplace=True)
(32): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(33): ReLU(inplace=True)
(34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(35): ReLU(inplace=True)
(36): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)

```

Created a helper function in order to upload any image type and sizes.

```

def load_image(img_path, max_size=400, shape=None):
    ''' Load in and transform an image, making sure the image
        is <= 400 pixels in the x-y dims.'''

    image = Image.open(img_path).convert('RGB')

    # large images will slow down processing
    if max(image.size) > max_size:
        size = max_size
    else:
        size = max(image.size)

    if shape is not None:
        size = shape

    in_transform = transforms.Compose([
        transforms.Resize(size),
        transforms.ToTensor(),
        transforms.Normalize((0.485, 0.456, 0.406),
                              (0.229, 0.224, 0.225))])

    # discard the transparent, alpha channel (that's the :3) and add the batch dimension
    image = in_transform(image)[:3,:,:].unsqueeze(0)

    return image

```

```

# load in content and style image
content = load_image('Technocore.jpg').to(device)
# Resize style to match content, makes code easier
style = load_image('VanGogh.jpg', shape=content.shape[-2:]).to(device)

```

```
# helper function for un-normalizing an image
# and converting it from a Tensor image to a NumPy image for display
def im_convert(tensor):
    """ Display a tensor as an image. """

    image = tensor.to("cpu").clone().detach()
    image = image.numpy().squeeze()
    image = image.transpose(1,2,0)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = image.clip(0, 1)

    return image
```

```
# display the images
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 10))
# content and style imgs side-by-side
ax1.imshow(im_convert(content))
ax1.set_title("Content Image", fontsize = 20)
ax2.imshow(im_convert(style))
ax2.set_title("Style Image", fontsize = 20)
plt.show()
```



```
# print out VGG19 structure to names of various layers
print(vgg)
```

```
Sequential(
  (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (1): ReLU(inplace=True)
  (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (3): ReLU(inplace=True)
  (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (6): ReLU(inplace=True)
  (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (8): ReLU(inplace=True)
  (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (11): ReLU(inplace=True)
  (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (13): ReLU(inplace=True)
  (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (15): ReLU(inplace=True)
  (16): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (17): ReLU(inplace=True)
  (18): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (19): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (20): ReLU(inplace=True)
  (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (22): ReLU(inplace=True)
  (23): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (24): ReLU(inplace=True)
  (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (26): ReLU(inplace=True)
  (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (29): ReLU(inplace=True)
  (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (31): ReLU(inplace=True)
  (32): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (33): ReLU(inplace=True)
  (34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (35): ReLU(inplace=True)
  (36): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
```

```
def get_features(image, model, layers=None):
    """ Run an image forward through a model and get the features for
        a set of layers. Default layers are for VGGNet matching Gatys et al (2016)
    """

    ## TODO: Complete mapping layer names of PyTorch's VGGNet to names from the paper
    ## Need the layers for the content and style representations of an image
    if layers is None:
        layers = {'0': 'conv1_1',
                  '5': 'conv2_1',
                  '10': 'conv3_1',
                  '19': 'conv4_1',
                  '21': 'conv4_2', ## content representation
                  '28': 'conv5_1'}

    features = {}
    x = image
    # model._modules is a dictionary holding each module in the model
    for name, layer in model._modules.items():
        x = layer(x)
        if name in layers:
            features[layers[name]] = x

    return features
```

```
def gram_matrix(tensor):
    """ Calculate the Gram Matrix of a given tensor
        Gram Matrix: https://en.wikipedia.org/wiki/Gramian\_matrix
    """

    # get the batch_size, depth, height, and width of the Tensor
    _, d, h, w = tensor.size()

    # reshape so we're multiplying the features for each channel
    tensor = tensor.view(d, h * w)

    # calculate the gram matrix
    gram = torch.mm(tensor, tensor.t())

    return gram
```

```
# get content and style features only once before training
content_features = get_features(content, vgg)
style_features = get_features(style, vgg)

# calculate the gram matrices for each layer of our style representation
style_grams = {layer: gram_matrix(style_features[layer]) for layer in style_features}

# create a third "target" image and prep it for change
# it is a good idea to start of with the target as a copy of our *content* image
# then iteratively change its style
target = content.clone().requires_grad_(True).to(device)
```

```
# weights for each style layer
# weighting earlier layers more will result in *larger* style artifacts
# notice we are excluding `conv4_2` our content representation
style_weights = {'conv1_1': 1.,
                  'conv2_1': 0.75,
                  'conv3_1': 0.2,
                  'conv4_1': 0.2,
                  'conv5_1': 0.2}

content_weight = 1 # alpha
style_weight = 1e9 # beta
```

```
# for displaying the target image, intermittently
show_every = 400

# iteration hyperparameters
optimizer = optim.Adam([target], lr=0.003)
steps = 5000 # decide how many iterations to update your image (5000)

for ii in range(1, steps+1):

    # get the features from your target image
    target_features = get_features(target, vgg)

    # the content loss
    content_loss = torch.mean((target_features['conv4_2'] - content_features['conv4_2'])**2)
```



```

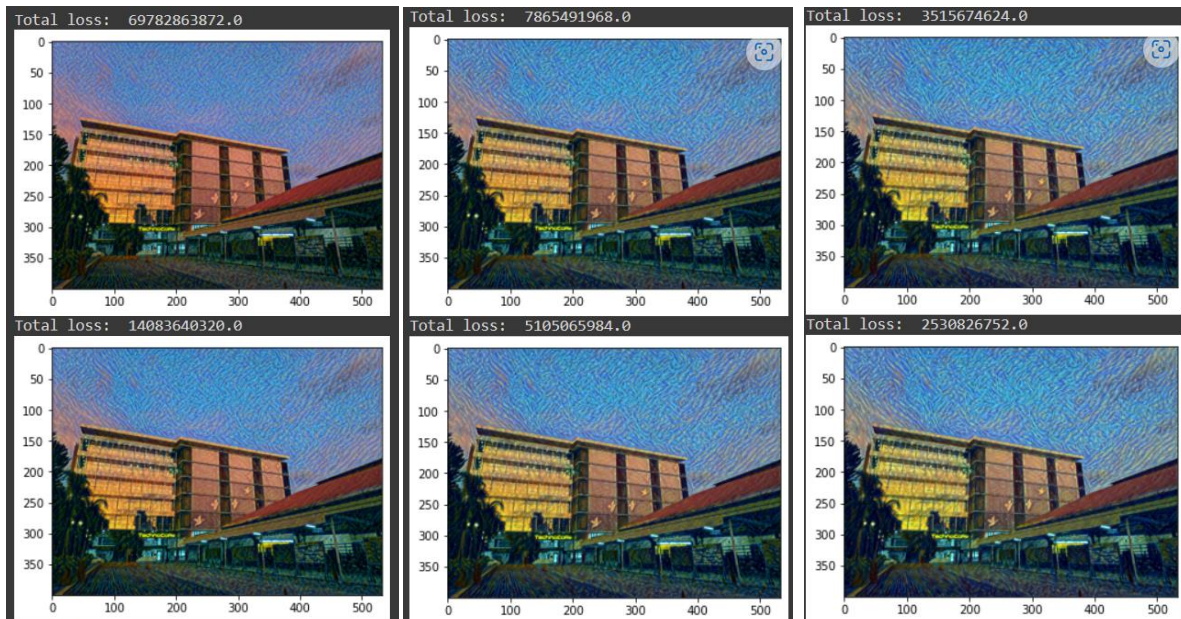
# the style loss
# initialize the style loss to 0
style_loss = 0
# then add to it for each layer's gram matrix loss
for layer in style_weights:
    # get the "target" style representation for the layer
    target_feature = target_features[layer]
    target_gram = gram_matrix(target_feature)
    _, d, h, w = target_feature.shape
    # get the "style" style representation
    style_gram = style_grams[layer]
    # the style loss for one layer, weighted appropriately
    layer_style_loss = style_weights[layer] * torch.mean((target_gram - style_gram)**2)
    # add to the style loss
    style_loss += layer_style_loss / (d * h * w)

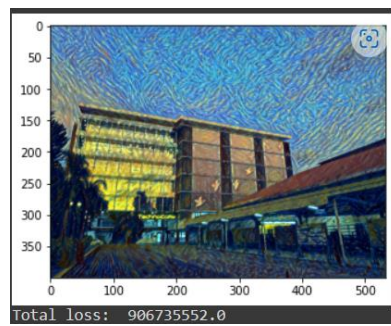
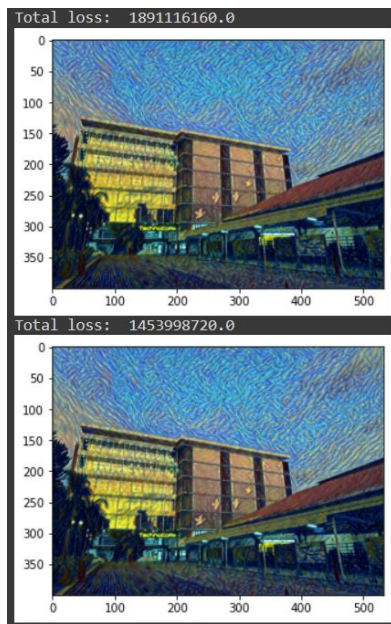
# calculate the *total* loss
total_loss = content_weight * content_loss + style_weight * style_loss

# update your target image
optimizer.zero_grad()
total_loss.backward()
optimizer.step()

# display intermediate images and print the loss
if ii % show_every == 0:
    print('Total loss: ', total_loss.item())
    plt.imshow(im_convert(target))
    plt.show()

```





```
# display content and final, target image
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(15, 15))
ax1.imshow(im_convert(content))
ax1.set_title("Content Image", fontsize = 20)
ax2.imshow(im_convert(target))
ax2.set_title("Stylized Target Image", fontsize = 20)
ax1.grid(False)
ax2.grid(False)
# Hide axes ticks
ax1.set_xticks([])
ax1.set_yticks([])
ax2.set_xticks([])
ax2.set_yticks([])
plt.show()
```

Results:

Pablo Picasso:



Base Image: TIP TechnoCore



Style Image: Mediterranean



Stylized Image

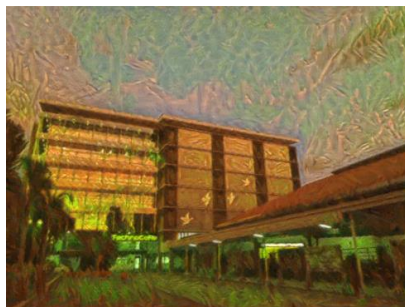
Fernando Amorsolo:



Base Image: TIP TechnoCore



Style Image:



Stylized Image