

+ Code + Text Copy to Drive

RAM Disk Editing ▾

▼ Ungraded Lab: Neural Style Transfer

This lab will demonstrate neural style transfer using a pretrained [VGG19](#) model as the feature extractor. You will see how to get outputs from specific layers of the model to compute the style and content loss, then use that to update the content image. The techniques you use here will be very useful in this week's programming assignment. You will also revisit this lab after Lesson 2 of this week when you learn about the total variation loss.

▼ Imports

```
✓ [1] try:
    # %tensorflow_version only exists in Colab.
    %tensorflow_version 2.x
except Exception:
    pass

import tensorflow as tf

import matplotlib.pyplot as plt
import numpy as np
from keras import backend as K

from imageio import mimwrite
from IPython.display import display as display_fn
from IPython.display import Image, clear_output
```

▼ Utilities

We've provided some utility functions below to help in loading, visualizing, and preprocessing the images.

```
✓ [2] def tensor_to_image(tensor):
    '''converts a tensor to an image'''
    tensor_shape = tf.shape(tensor)
    number_elem_shape = tf.shape(tensor_shape)
    if number_elem_shape > 3:
        assert tensor_shape[0] == 1
        tensor = tensor[0]
    return tf.keras.preprocessing.image.array_to_img(tensor)

def load_img(path_to_img):
    '''loads an image as a tensor and scales it to 512 pixels'''
    max_dim = 512
    image = tf.io.read_file(path_to_img)
    image = tf.image.decode_jpeg(image)
    image = tf.image.convert_image_dtype(image, tf.float32)

    shape = tf.shape(image)[::1]
    shape = tf.cast(tf.shape(image)[::1], tf.float32)
    long_dim = max(shape)
    scale = max_dim / long_dim

    new_shape = tf.cast(shape * scale, tf.int32)

    image = tf.image.resize(image, new_shape)
    image = image[tf.newaxis, :]
    image = tf.image.convert_image_dtype(image, tf.uint8)

    return image

def load_images(content_path, style_path):
    '''loads the content and path images as tensors'''
    content_image = load_img("{}".format(content_path))
    style_image = load_img("{}".format(style_path))

    return content_image, style_image

def imshow(image, title=None):
    '''displays an image with a corresponding title'''
    if len(image.shape) > 3:
        image = tf.squeeze(image, axis=0)

    plt.imshow(image)
    if title:
        plt.title(title)

def show_images_with_objects(images, titles=[]):
    '''displays a row of images with corresponding titles'''
    if len(images) != len(titles):
        return

    plt.figure(figsize=(20, 12))
    for idx, (image, title) in enumerate(zip(images, titles)):
        plt.subplot(1, len(images), idx + 1)
        plt.xticks([])
        plt.yticks([])
        imshow(image, title)

def display_gif(gif_path):
    '''displays the generated images as an animated gif'''
    with open(gif_path, 'rb') as f:
```

```

display_fn(Image(data=f.read(), format='png'))

def create_gif(gif_path, images):
    '''creates animation of generated images'''
    mimsave(gif_path, images, fps=1)

    return gif_path

def clip_image_values(image, min_value=0.0, max_value=255.0):
    '''clips the image pixel values by the given min and max'''
    return tf.clip_by_value(image, clip_value_min=min_value, clip_value_max=max_value)

def preprocess_image(image):
    '''centers the pixel values of a given image to use with VGG-19'''
    image = tf.cast(image, dtype=tf.float32)
    image = tf.keras.applications.vgg19.preprocess_input(image)

    return image

```

▼ Download Images

You will download a few images and you can choose which one will be the content and style image. We will set the default style and content image to the images you saw in class.

```

[3] IMAGE_DIR = 'images'

# create directory
!mkdir {IMAGE_DIR}

# download images to the directory you just created
!wget -q -O ./images/cafe.jpg https://cdn.pixabay.com/photo/2018/07/14/15/27/cafe-3537801_1280.jpg
!wget -q -O ./images/swan.jpg https://cdn.pixabay.com/photo/2017/02/28/23/00/swan-2107052_1280.jpg
!wget -q -O ./images/tnj.jpg https://i.dawn.com/large/2019/10/5db6a03a4c7e3.jpg
!wget -q -O ./images/rudolph.jpg https://cdn.pixabay.com/photo/2015/09/22/12/21/rudolph-951494_1280.jpg
!wget -q -O ./images/dynamite.jpg https://cdn.pixabay.com/photo/2015/10/13/02/59/animals-985500_1280.jpg
!wget -q -O ./images/painting.jpg https://storage.googleapis.com/download.tensorflow.org/example_images/Vassily_Kandinsky%2C_1913_-_Composition_7.jpg

print("image files you can choose from:")
!ls images

```

image files you can choose from:
cafe.jpg dynamite.jpg painting.jpg rudolph.jpg swan.jpg tnj.jpg

```

[4] # set default images
content_path = f'{IMAGE_DIR}/swan.jpg'
style_path = f'{IMAGE_DIR}/painting.jpg'

```

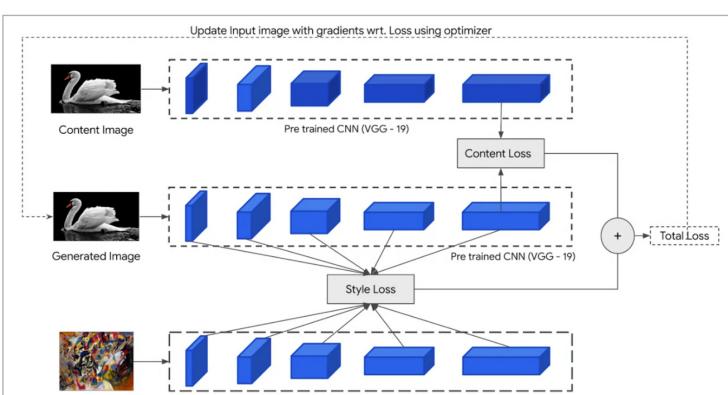
```

[5] # display the content and style image
content_image, style_image = load_images(content_path, style_path)
show_images_with_objects([content_image, style_image],
titles=[f'content image: {content_path}',
f'style image: {style_path}'])

```



▼ Build the model



As mentioned, you will be using the VGG-19 model as the feature extractor. You will feed in the style and content image and depending on the computed losses, a new image will be generated which has elements of both the content and style image. You can download a temporary copy of the model just for inspecting the layers that are available for you to use.

```
✓ [6] # clear session to make layer naming consistent when re-running this cell
      K.clear_session()

      # download the vgg19 model and inspect the layers
      tmp_vgg = tf.keras.applications.VGG19()
      tmp_vgg.summary()

      # delete temporary variable
      del tmp_vgg



| Layer (type)               | Output Shape          | Param #   |
|----------------------------|-----------------------|-----------|
| input_1 (InputLayer)       | [None, 224, 224, 3]   | 0         |
| block1_conv1 (Conv2D)      | (None, 224, 224, 64)  | 1792      |
| block1_conv2 (Conv2D)      | (None, 224, 224, 64)  | 36928     |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64)  | 0         |
| block2_conv1 (Conv2D)      | (None, 112, 112, 128) | 73856     |
| block2_conv2 (Conv2D)      | (None, 112, 112, 128) | 147584    |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128)   | 0         |
| block3_conv1 (Conv2D)      | (None, 56, 56, 256)   | 295168    |
| block3_conv2 (Conv2D)      | (None, 56, 56, 256)   | 590080    |
| block3_conv3 (Conv2D)      | (None, 56, 56, 256)   | 590080    |
| block3_conv4 (Conv2D)      | (None, 56, 56, 256)   | 590080    |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256)   | 0         |
| block4_conv1 (Conv2D)      | (None, 28, 28, 512)   | 1180160   |
| block4_conv2 (Conv2D)      | (None, 28, 28, 512)   | 2359808   |
| block4_conv3 (Conv2D)      | (None, 28, 28, 512)   | 2359808   |
| block4_conv4 (Conv2D)      | (None, 28, 28, 512)   | 2359808   |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512)   | 0         |
| block5_conv1 (Conv2D)      | (None, 14, 14, 512)   | 2359808   |
| block5_conv2 (Conv2D)      | (None, 14, 14, 512)   | 2359808   |
| block5_conv3 (Conv2D)      | (None, 14, 14, 512)   | 2359808   |
| block5_conv4 (Conv2D)      | (None, 14, 14, 512)   | 2359808   |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512)     | 0         |
| flatten (Flatten)          | (None, 25088)         | 0         |
| fc1 (Dense)                | (None, 4096)          | 102764544 |
| fc2 (Dense)                | (None, 4096)          | 16781312  |
| predictions (Dense)        | (None, 1000)          | 4097000   |


Total params: 143,667,240
Trainable params: 143,667,240
Non-trainable params: 0
```

Choose intermediate layers from the network to extract the style and content of the image:

- For the style layers, you will use the first layer of each convolutional block.
- For the content layer, you will use the second convolutional layer of the last convolutional block (just one layer)

```
✓ [7] # style layers of interest
      style_layers = ['block1_conv1',
                      'block2_conv1',
                      'block3_conv1',
                      'block4_conv1',
                      'block5_conv1']

      # choose the content layer and put in a list
      content_layers = ['block5_conv2']

      # combine the two lists (put the style layers before the content layers)
      output_layers = style_layers + content_layers

      # declare auxiliary variables holding the number of style and content layers
      NUM_CONTENT_LAYERS = len(content_layers)
      NUM_STYLE_LAYERS = len(style_layers)
```

Define your model to take the same input as the standard VGG-19 model, and output just the selected content and style layers.

```
✓ [8] def vgg_model(layer_names):
      """ Creates a vgg model that outputs the style and content layer activations.

      Args:
          layer_names: a list of strings, representing the names of the desired content and style layers

      Returns:
```

```
A model that takes the regular vgg19 input and outputs just the content and style layers.
```

```
"""
# load the the pretrained VGG, trained on imagenet data
vgg = tf.keras.applications.vgg19.VGG19(include_top=False, weights='imagenet')

# freeze the weights of the model's layers (make them not trainable)
vgg.trainable = False

# create a list of layer objects that are specified by layer_names
outputs = [vgg.get_layer(name).output for name in layer_names]

# create the model that outputs content and style layers only
model = tf.keras.Model(inputs=vgg.input, outputs=outputs)

return model
```

Create an instance of the model using the function that you just defined.

```
[9] # clear session to make layer naming consistent if re-running the cell
K.clear_session()

# create a vgg-19 model
vgg = vgg_model(output_layers)
vgg.summary()

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80142336/80134624 [=====] - 1s 0us/step
Model: "model"

Layer (type)          Output Shape         Param #
=================================================================
input_2 (InputLayer)   [(None, None, None, 3)]  0
block1_conv1 (Conv2D)  (None, None, None, 64)   1792
block1_conv2 (Conv2D)  (None, None, None, 64)   36928
block1_pool (MaxPooling2D) (None, None, None, 64)  0
block2_conv1 (Conv2D)  (None, None, None, 128)  73856
block2_conv2 (Conv2D)  (None, None, None, 128)  147584
block2_pool (MaxPooling2D) (None, None, None, 128)  0
block3_conv1 (Conv2D)  (None, None, None, 256)  295168
block3_conv2 (Conv2D)  (None, None, None, 256)  590080
block3_conv3 (Conv2D)  (None, None, None, 256)  590080
block3_conv4 (Conv2D)  (None, None, None, 256)  590080
block3_pool (MaxPooling2D) (None, None, None, 256)  0
block4_conv1 (Conv2D)  (None, None, None, 512)  1180160
block4_conv2 (Conv2D)  (None, None, None, 512)  2359808
block4_conv3 (Conv2D)  (None, None, None, 512)  2359808
block4_conv4 (Conv2D)  (None, None, None, 512)  2359808
block4_pool (MaxPooling2D) (None, None, None, 512)  0
block5_conv1 (Conv2D)  (None, None, None, 512)  2359808
block5_conv2 (Conv2D)  (None, None, None, 512)  2359808
=====
Total params: 15,304,768
Trainable params: 0
Non-trainable params: 15,304,768
```

▼ Define the loss functions

Next, you will define functions to compute the losses required for generating the new image. These would be the:

- style loss
- content loss
- total loss (combination of style and content loss)

▼ Calculate style loss

The style loss is the average of the squared differences between the features and targets.

```
[10] def get_style_loss(features, targets):
    """Expects two images of dimension h, w, c

    Args:
        features: tensor with shape: (height, width, channels)
        targets: tensor with shape: (height, width, channels)

    Returns:
        style loss (scalar)
    """
    # get the average of the squared errors
    style_loss = tf.reduce_mean(tf.square(features - targets))

    return style_loss
```

▼ Calculate content loss

The content loss will be the sum of the squared error between the features and targets, then multiplied by a scaling factor (0.5).

```

✓ [11] def get_content_loss(features, targets):
    """Expects two images of dimension h, w, c

    Args:
        features: tensor with shape: (height, width, channels)
        targets: tensor with shape: (height, width, channels)

    Returns:
        content loss (scalar)
    """
    # get the sum of the squared error multiplied by a scaling factor
    content_loss = 0.5 * tf.reduce_sum(tf.square(features - targets))

    return content_loss

```

▼ Calculate the gram matrix

Use `tf.linalg.einsum` to calculate the gram matrix for an input tensor.

- In addition, calculate the scaling factor `num_locations` and divide the gram matrix calculation by `num_locations`.

$$\text{num locations} = \text{height} \times \text{width}$$

```

✓ [12] def gram_matrix(input_tensor):
    """ Calculates the gram matrix and divides by the number of locations
    Args:
        input_tensor: tensor of shape (batch, height, width, channels)

    Returns:
        scaled_gram: gram matrix divided by the number of locations
    """

    # calculate the gram matrix of the input tensor
    gram = tf.linalg.einsum('bijc,bijd->bcd', input_tensor, input_tensor)

    # get the height and width of the input tensor
    input_shape = tf.shape(input_tensor)
    height = input_shape[1]
    width = input_shape[2]

    # get the number of locations (height times width), and cast it as a tf.float32
    num_locations = tf.cast(height * width, tf.float32)

    # scale the gram matrix by dividing by the number of locations
    scaled_gram = gram / num_locations

    return scaled_gram

```

▼ Get the style image features

Given the style image as input, you'll get the style features of the custom VGG model that you just created using `vgg_model()`.

- You will first preprocess the image using the given `preprocess_image()` function.
- You will then get the outputs of the vgg model.
- From the outputs, just get the style feature layers and not the content feature layer.

You can run the following code to check the order of the layers in your custom vgg model:

```

✓ [13] tmp_layer_list = [layer.output for layer in vgg.layers]
tmp_layer_list

[<KerasTensor: shape=(None, None, None, 3) dtype=float32 (created by layer 'input_2')>,
 <KerasTensor: shape=(None, None, None, 64) dtype=float32 (created by layer 'block1_conv1')>,
 <KerasTensor: shape=(None, None, None, 64) dtype=float32 (created by layer 'block1_conv2')>,
 <KerasTensor: shape=(None, None, None, 64) dtype=float32 (created by layer 'block1_pool')>,
 <KerasTensor: shape=(None, None, 128) dtype=float32 (created by layer 'block2_conv1')>,
 <KerasTensor: shape=(None, None, 128) dtype=float32 (created by layer 'block2_conv2')>,
 <KerasTensor: shape=(None, None, 128) dtype=float32 (created by layer 'block2_pool')>,
 <KerasTensor: shape=(None, None, None, 256) dtype=float32 (created by layer 'block3_conv1')>,
 <KerasTensor: shape=(None, None, None, 256) dtype=float32 (created by layer 'block3_conv2')>,
 <KerasTensor: shape=(None, None, None, 256) dtype=float32 (created by layer 'block3_conv3')>,
 <KerasTensor: shape=(None, None, None, 256) dtype=float32 (created by layer 'block3_conv4')>,
 <KerasTensor: shape=(None, None, None, 256) dtype=float32 (created by layer 'block3_pool')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block4_conv1')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block4_conv2')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block4_conv3')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block4_conv4')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block4_pool')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block5_conv1')>,
 <KerasTensor: shape=(None, None, None, 512) dtype=float32 (created by layer 'block5_conv2')>]

```

- For each style layer, calculate the gram matrix. Store these results in a list and return it.

```

✓ [14] def get_style_image_features(image):
    """ Get the style image features

    Args:
        image: an input image

    Returns:
        gram_style_features: the style features as gram matrices
    """

    # preprocess the image using the given preprocessing function
    preprocessed_style_image = preprocess_image(image)

    # get the outputs from the custom vgg model that you created using vgg_model()
    outputs = vgg(preprocessed_style_image)

    # Get just the style feature layers (exclude the content layer)
    style_outputs = outputs[:NUM_STYLE_LAYERS]

    # for each style layer, calculate the gram matrix for that layer and store these results in a list
    gram_style_features = [gram_matrix(style_layer) for style_layer in style_outputs]

```

```
return gram_style_features
```

▼ Get content image features

Now you will get the content features of an image.

- You can follow a similar process as you did with `get_style_image_features()`.
- You will not calculate the gram matrix of these features.

```
✓ [15] def get_content_image_features(image):
    """ Get the content image features

    Args:
        image: an input image

    Returns:
        content_outputs: the content features of the image
    """
    # preprocess the image
    preprocessed_content_image = preprocess_image(image)

    # get the outputs from the vgg model
    outputs = vgg(preprocessed_content_image)

    # get the content layers of the outputs
    content_outputs = outputs[NUM_STYLE_LAYERS:]

    # return the content layer outputs of the content image
    return content_outputs
```

▼ Calculate the style and content loss

The total loss is given by $L_{total} = \beta L_{style} + \alpha L_{content}$, where β and α are weights we will give to the content and style features to generate the new image. See how it is implemented in the function below.

```
✓ [16] def get_style_content_loss(style_targets, style_outputs, content_targets,
                                    content_outputs, style_weight, content_weight):
    """ Combine the style and content loss

    Args:
        style_targets: style features of the style image
        style_outputs: style features of the generated image
        content_targets: content features of the content image
        content_outputs: content features of the generated image
        style_weight: weight given to the style loss
        content_weight: weight given to the content loss

    Returns:
        total_loss: the combined style and content loss
    """

    # sum of the style losses
    style_loss = tf.add_n([get_style_loss(style_output, style_target)
                          for style_output, style_target in zip(style_outputs, style_targets)])

    # Sum up the content losses
    content_loss = tf.add_n([get_content_loss(content_output, content_target)
                            for content_output, content_target in zip(content_outputs, content_targets)])

    # scale the style loss by multiplying by the style weight and dividing by the number of style layers
    style_loss = style_loss * style_weight / NUM_STYLE_LAYERS

    # scale the content loss by multiplying by the content weight and dividing by the number of content layers
    content_loss = content_loss * content_weight / NUM_CONTENT_LAYERS

    # sum up the style and content losses
    total_loss = style_loss + content_loss

    return total_loss
```

▼ Generate the Stylized Image

You will now define helper functions to generate the new image given the total loss.

▼ Calculate gradients

First is the function to calculate the gradients. The values here will be used to update the generated image to have more of the style and content features.

Note: If you are still in Lesson 1, please disregard the `var_weight` parameter. That will be defined and discussed in Lesson 2.

```
✓ [17] def calculate_gradients(image, style_targets, content_targets,
                                style_weight, content_weight, var_weight):
    """ Calculate the gradients of the loss with respect to the generated image

    Args:
        image: generated image
        style_targets: style features of the style image
        content_targets: content features of the content image
        style_weight: weight given to the style loss
        content_weight: weight given to the content loss
        var_weight: weight given to the total variation loss

    Returns:
        gradients: gradients of the loss with respect to the input image
    """
    with tf.GradientTape() as tape:

        # get the style image features
        style_features = get_style_image_features(image)
```

```

# get the content image features
content_features = get_content_image_features(image)

# get the style and content loss
loss = get_style_content_loss(style_targets, style_features, content_targets,
                             content_features, style_weight, content_weight)

# calculate gradients of loss with respect to the image
gradients = tape.gradient(loss, image)

return gradients

```

▼ Update the image with the style

Similar to model training, you will use an optimizer to update the original image from the computed gradients. Since we're dealing with images, we want to clip the values to the range we expect. That would be [0, 255] in this case.

```

[18] def update_image_with_style(image, style_targets, content_targets, style_weight,
                                 var_weight, content_weight, optimizer):
    """
    Args:
        image: generated image
        style_targets: style features of the style image
        content_targets: content features of the content image
        style_weight: weight given to the style loss
        content_weight: weight given to the content loss
        var_weight: weight given to the total variation loss
        optimizer: optimizer for updating the input image
    """

    # calculate gradients using the function that you just defined.
    gradients = calculate_gradients(image, style_targets, content_targets,
                                    style_weight, content_weight, var_weight)

    # apply the gradients to the given image
    optimizer.apply_gradients([(gradients, image)])

    # clip the image using the utility clip_image_values() function
    image.assign(clip_image_values(image, min_value=0.0, max_value=255.0))

```

▼ Style Transfer

You can now define the main loop. This will use the previous functions you just defined to generate the stylized content image. It does so incrementally based on the computed gradients and the number of epochs. Visualizing the output at each epoch is also useful so you can quickly see if the style transfer is working.

```

[19] def fit_style_transfer(style_image, content_image, style_weight=1e-2, content_weight=1e-4,
                           var_weight=0, optimizer='adam', epochs=1, steps_per_epoch=1):
    """
    Performs neural style transfer.
    Args:
        style_image: image to get style features from
        content_image: image to stylize
        style_targets: style features of the style image
        content_targets: content features of the content image
        style_weight: weight given to the style loss
        content_weight: weight given to the content loss
        var_weight: weight given to the total variation loss
        optimizer: optimizer for updating the input image
        epochs: number of epochs
        steps_per_epoch = steps per epoch
    Returns:
        generated_image: generated image at final epoch
        images: collection of generated images per epoch
    """

    images = []
    step = 0

    # get the style image features
    style_targets = get_style_image_features(style_image)

    # get the content image features
    content_targets = get_content_image_features(content_image)

    # initialize the generated image for updates
    generated_image = tf.cast(content_image, dtype=tf.float32)
    generated_image = tf.Variable(generated_image)

    # collect the image updates starting from the content image
    images.append(content_image)

    # incrementally update the content image with the style features
    for n in range(epochs):
        for m in range(steps_per_epoch):
            step += 1

            # Update the image with the style using the function that you defined
            update_image_with_style(generated_image, style_targets, content_targets,
                                   style_weight, var_weight, content_weight, optimizer)

            print(".", end='')

            if (m + 1) % 10 == 0:
                images.append(generated_image)

    # display the current stylized image
    clear_output(wait=True)
    display_image = tensor_to_image(generated_image)
    display_fn(display_image)

    # append to the image collection for visualization later

```

```

    images.append(generated_image)
    print("Train step: {}".format(step))

    # convert to uint8 (expected dtype for images with pixels in the range [0,255])
    generated_image = tf.cast(generated_image, dtype=tf.uint8)

    return generated_image, images

```

▼ Try it out!

With all things setup, the neural style transfer is now ready to run. If you want to change the given parameters, we advise that you do so only after you have also completed Lesson 2 and its corresponding exercise at the end of this notebook.

```

✓ [20] # define style and content weight
style_weight = 2e-2
content_weight = 1e-2

# define optimizer, learning rate decreases per epoch.
adam = tf.optimizers.Adam(
    tf.keras.optimizers.schedules.ExponentialDecay(
        initial_learning_rate=20.0, decay_steps=100, decay_rate=0.50
    )
)

# start the neural style transfer
stylized_image, display_images = fit_style_transfer(style_image=style_image, content_image=content_image,
                                                    style_weight=style_weight, content_weight=content_weight,
                                                    var_weight=0, optimizer=adam, epochs=10, steps_per_epoch=100)

```



Train step: 1000

```

✓ [21] # display GIF of Intermediate Outputs
48s
GIF_PATH = 'style_transfer.gif'
gif_images = [np.squeeze(image.numpy().astype(np.uint8), axis=0) for image in display_images]
gif_path = create_gif(GIF_PATH, gif_images)
display_gif(gif_path)

```



End of Lesson 1 ungraded lab

This concludes the demo for Lesson 1. Please go back to the classroom and watch Lesson 2 regarding the total variation loss. Then you can continue on to the next section below.

▼ Total variation loss

One downside to the implementation above is that it produces a lot of high frequency artifacts. You can see this when you plot the frequency variations of the image. We've defined a few helper functions below to do that.

```

✓ [22] # Plot Utilities
0s
def high_pass_x_y(image):
    x_var = image[:, :, 1:, :] - image[:, :, :-1, :]
    y_var = image[:, 1:, :, :] - image[:, :-1, :, :]

    return x_var, y_var

def plot_deltas_for_single_image(x_deltas, y_deltas, name="Original", row=1):
    plt.figure(figsize=(14, 10))
    plt.subplot(row, 2, 1)
    plt.yticks([])
    plt.xticks([])

    clipped_y_deltas = clip_image_values(2*y_deltas+0.5, min_value=0.0, max_value=1.0)
    imshow(clipped_y_deltas, "Horizontal Deltas: {}".format(name))

    plt.subplot(row, 2, 2)
    plt.yticks([])
    plt.xticks([])

```

```

clipped_x_deltas = clip_image_values(2*x_deltas+0.5, min_value=0.0, max_value=1.0)
imshow(clipped_x_deltas, "Vertical Deltas: {}".format(name))

def plot_deltas(original_image_deltas, stylized_image_deltas):
    orig_x_deltas, orig_y_deltas = original_image_deltas

    stylized_x_deltas, stylized_y_deltas = stylized_image_deltas

    plot_deltas_for_single_image(orig_x_deltas, orig_y_deltas, name="Original")
    plot_deltas_for_single_image(stylized_x_deltas, stylized_y_deltas, name="Stylized Image", row=2)

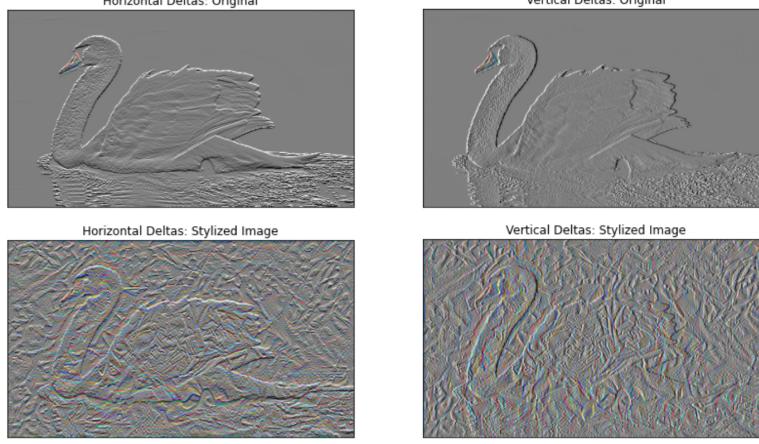
✓ [23] # Display the frequency variations

```

```
0s original_x_deltas, original_y_deltas = high_pass_x_y(
    tf.image.convert_image_dtype(content_image, dtype=tf.float32))

stylized_image_x_deltas, stylized_image_y_deltas = high_pass_x_y(
    tf.image.convert_image_dtype(stylized_image, dtype=tf.float32))

plot_deltas((original_x_deltas, original_y_deltas), (stylized_image_x_deltas, stylized_image_y_deltas))
```



We can decrease these using an explicit regularization term on the high frequency components of the image. In style transfer, this is often called the *total variation loss*. Let's define the `calculate_gradients()` function again but this time with a regularization parameter to compute the total variation loss. We've added the total variation weight as a function parameter (i.e. `var_weight`) so you can easily adjust it if you want.

```

✓ [24] def calculate_gradients(image, style_targets, content_targets,
                               style_weight, content_weight, var_weight):
    """ Calculate the gradients of the loss with respect to the generated image
    Args:
        image: generated image
        style_targets: style features of the style image
        content_targets: content features of the content image
        style_weight: weight given to the style loss
        content_weight: weight given to the content loss
        var_weight: weight given to the total variation loss

    Returns:
        gradients: gradients of the loss with respect to the input image
    """
    with tf.GradientTape() as tape:

        # get the style image features
        style_features = get_style_image_features(image)

        # get the content image features
        content_features = get_content_image_features(image)

        # get the style and content loss
        loss = get_style_content_loss(style_targets, style_features, content_targets,
                                      content_features, style_weight, content_weight)

        # add the total variation loss
        loss += var_weight*tf.image.total_variation(image)

        # calculate gradients of loss with respect to the image
        gradients = tape.gradient(loss, image)

    return gradients

```

▼ Re-run the optimization

Let's run the style transfer loop again this time taking into account the total variation loss.

```

✓ [25] style_weight = 2e-2
content_weight = 1e-2
var_weight = 2

adam = tf.optimizers.Adam(
    tf.keras.optimizers.schedules.ExponentialDecay(
        initial_learning_rate=20.0, decay_steps=100, decay_rate=0.50
    )
)

stylized_image_reg, display_images_reg = fit_style_transfer(style_image=style_image, content_image=content_image,
                                                          style_weight=style_weight, content_weight=content_weight,
                                                          var_weight=var_weight, optimizer=adam, epochs=10, steps_per_epoch=100)

```



Train step: 1000

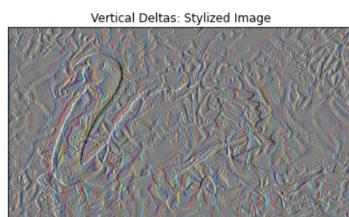
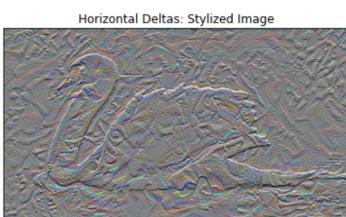
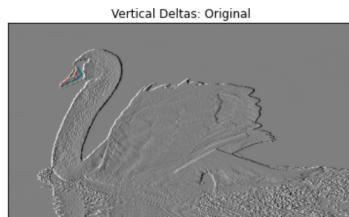
```
✓ [26] # Display GIF
41s   GIF_PATH = 'style_transfer_reg.gif'
    gif_images_reg = [np.squeeze(image.numpy().astype(np.uint8), axis=0) for image in display_images_reg]
    gif_path_reg = create_gif(GIF_PATH, gif_images_reg)
    display_gif(gif_path_reg)
```



```
✓ [27] # Display Frequency Variations
0s
original_x_deltas, original_y_deltas = high_pass_x_y(
    tf.image.convert_image_dtype(content_image, dtype=tf.float32))

stylized_image_reg_x_deltas, stylized_image_reg_y_deltas = high_pass_x_y(
    tf.image.convert_image_dtype(stylized_image_reg, dtype=tf.float32))

plot_deltas((original_x_deltas, original_y_deltas), (stylized_image_reg_x_deltas, stylized_image_reg_y_deltas))
```



Notice that the variations are generally smoother with the additional parameter. Here are the stylized images again with and without regularization for comparison.

```
✓ [28] show_images_with_objects([style_image, content_image, stylized_image], titles=['Style Image', 'Content Image', 'Stylized Image'])
```



```
✓ [29] show_images_with_objects([style_image, content_image, stylized_image_reg], titles=['Style Image', 'Content Image', 'Stylized Image with Regularization'])
```





Awesome work! You have now completed the labs for Neural Style Transfer!

✓ 0s completed at 3:06 PM

