```
import os
img_dir = '/tmp/nst'
if not os.path.exists(img_dir):
    os.makedirs(img_dir)
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/d/d7/Green_Sea_Turt
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/0/0a/The_Great_Wave
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/b/b4/Vassily_Kandir
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/0/00/Tuebingen_Neck
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/6/68/Pillars_of_cre
!wget --quiet -P /tmp/nst/ https://upload.wikimedia.org/wikipedia/commons/thumb/e/ea/Van_Gogh
```

```
import matplotlib.pyplot as plt
import matplotlib as mpl
mpl.rcParams['figure.figsize'] = (10,10)
mpl.rcParams['axes.grid'] = False

import numpy as np
from PIL import Image
import time
import functools


import tensorflow as tf

from tensorflow.python.keras.preprocessing import image as kp_image
from tensorflow.python.keras import models
from tensorflow.python.keras import losses
from tensorflow.python.keras import layers
from tensorflow.python.keras import backend as K
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info.

```
tf.enable_eager_execution()
print("Eager execution: {}".format(tf.executing_eagerly()))
```

```
Eager execution: True
```

```
# Set up some global values here
content_path = '/tmp/nst/Green_Sea_Turtle_grazing_seagrass.jpg'
style_path = '/tmp/nst/The_Great_Wave_off_Kanagawa.jpg'
```

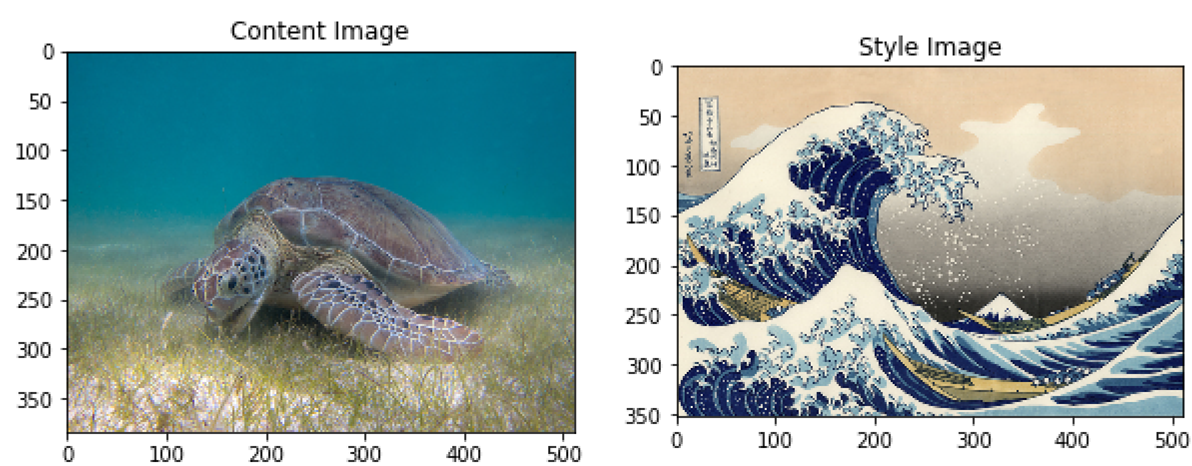
Visualize the input

```
def load_img(path_to_img):
  max_dim = 512
```

```
  max_dim = 512
  img = Image.open(path_to_img)

  long = max(img.size)
  scale = max_dim/long
  img = img.resize((round(img.size[0]*scale), round(img.size[1]*scale)), Image.ANTIALIAS)
  img = kp_image.img_to_array(img)

  # We need to broadcast the image array such that it has a batch dimension
  img = np.expand_dims(img, axis=0)
  return img
```

```
def imshow(img, title=None):
  # Remove the batch dimension
  out = np.squeeze(img, axis=0)
  # Normalize for display
  out = out.astype('uint8')
  plt.imshow(out)
  if title is not None:
    plt.title(title)
  plt.imshow(out)
```

```
plt.figure(figsize=(10,10))

content = load_img(content_path).astype('uint8')
style = load_img(style_path).astype('uint8')
plt.subplot(1, 2, 1)
imshow(content, 'Content Image')

plt.subplot(1, 2, 2)
imshow(style, 'Style Image')
plt.show()
```



Prepare the data

```
def load_and_process_img(path_to_img):
  img = load_img(path_to_img)
  img = tf.keras.applications.vgg19.preprocess_input(img)
  return img


def deprocess_img(processed_img):
  x = processed_img.copy()
  if len(x.shape) == 4:
    x = np.squeeze(x, 0)
  assert len(x.shape) == 3, ("Input to deprocess image must be an image of "
                             "dimension [1, height, width, channel] or [height, width, channe
  if len(x.shape) != 3:
    raise ValueError("Invalid input to deprocessing image")

  # perform the inverse of the preprocessiing step
  x[:, :, 0] += 103.939
  x[:, :, 1] += 116.779
  x[:, :, 2] += 123.68
  x = x[:, :, ::-1]

  x = np.clip(x, 0, 255).astype('uint8')
  return x


# Content layer where will pull our feature maps
content_layers = ['block5_conv2']

# Style layer we are interested in
style_layers = ['block1_conv1',
                'block2_conv1',
                'block3_conv1',
                'block4_conv1',
                'block5_conv1'
               ]

num_content_layers = len(content_layers)
num_style_layers = len(style_layers)
```

Build the Model

```
def get_model():
  """ Creates our model with access to intermediate layers.
```

```
  This function will load the VGG19 model and access the intermediate layers.
  These layers will then be used to create a new model that will take input image
  and return the outputs from these intermediate layers from the VGG model.

  Returns:
    returns a keras model that takes image inputs and outputs the style and
      content intermediate layers.
  """
  # Load our model. We load pretrained VGG, trained on imagenet data
  vgg = tf.keras.applications.vgg19.VGG19(include_top=False, weights='imagenet')
  vgg.trainable = False
  # Get output layers corresponding to style and content layers
  style_outputs = [vgg.get_layer(name).output for name in style_layers]
  content_outputs = [vgg.get_layer(name).output for name in content_layers]

  model_outputs = style_outputs + content_outputs
  # Build model
  return models.Model(vgg.input, model_outputs)
```

Computing content loss

```
def get_content_loss(base_content, target):
  return tf.reduce_mean(tf.square(base_content - target))
```

Computing Style Loss

```
def gram_matrix(input_tensor):
  # We make the image channels first
  channels = int(input_tensor.shape[-1])
  a = tf.reshape(input_tensor, [-1, channels])
  n = tf.shape(a)[0]
  gram = tf.matmul(a, a, transpose_a=True)
  return gram / tf.cast(n, tf.float32)

def get_style_loss(base_style, gram_target):
  """Expects two images of dimension h, w, c"""
  # height, width, num filters of each layer
  # We scale the loss at a given layer by the size of the feature map and the number of filte
  height, width, channels = base_style.get_shape().as_list()
  gram_style = gram_matrix(base_style)

  return tf.reduce_mean(tf.square(gram_style - gram_target))/ (4. * (channels ** 2) * (width
```

```
def get_feature_representations(model, content_path, style_path):
  """Helper function to compute our content and style feature representations.

  This function will simply load and preprocess both the content and style
  images from their path. Then it will feed them through the network to obtain
  the outputs of the intermediate layers.

  Arguments:
    model: The model that we are using.
    content_path: The path to the content image.
    style_path: The path to the style image

  Returns:
    returns the style features and the content features.
  """
  # Load our images in
  content_image = load_and_process_img(content_path)
  style_image = load_and_process_img(style_path)

  # batch compute content and style features
  style_outputs = model(style_image)
  content_outputs = model(content_image)


  # Get the style and content feature representations from our model
  style_features = [style_layer[0] for style_layer in style_outputs[:num_style_layers]]
  content_features = [content_layer[0] for content_layer in content_outputs[num_style_layers:
  return style_features, content_features
```

Computing the loss and gradients

```
def compute_loss(model, loss_weights, init_image, gram_style_features, content_features):
  """This function will compute the loss total loss.

  Arguments:
    model: The model that will give us access to the intermediate layers
    loss_weights: The weights of each contribution of each loss function.
      (style weight, content weight, and total variation weight)
    init_image: Our initial base image. This image is what we are updating with
      our optimization process. We apply the gradients wrt the loss we are
      calculating to this image.
    gram_style_features: Precomputed gram matrices corresponding to the
      defined style layers of interest.
    content_features: Precomputed outputs from defined content layers of
      interest.

  Returns:
    returns the total loss, style loss, content loss, and total variational loss
```

```
  """
  style_weight, content_weight = loss_weights

  # Feed our init image through our model. This will give us the content and
  # style representations at our desired layers. Since we're using eager
  # our model is callable just like any other function!
  model_outputs = model(init_image)

  style_output_features = model_outputs[:num_style_layers]
  content_output_features = model_outputs[num_style_layers:]

  style_score = 0
  content_score = 0

  # Accumulate style losses from all layers
  # Here, we equally weight each contribution of each loss layer
  weight_per_style_layer = 1.0 / float(num_style_layers)
  for target_style, comb_style in zip(gram_style_features, style_output_features):
    style_score += weight_per_style_layer * get_style_loss(comb_style[0], target_style)

  # Accumulate content losses from all layers
  weight_per_content_layer = 1.0 / float(num_content_layers)
  for target_content, comb_content in zip(content_features, content_output_features):
    content_score += weight_per_content_layer* get_content_loss(comb_content[0], target_conte

  style_score *= style_weight
  content_score *= content_weight

  # Get total loss
  loss = style_score + content_score
  return loss, style_score, content_score


def compute_grads(cfg):
  with tf.GradientTape() as tape:
    all_loss = compute_loss(**cfg)
  # Compute gradients wrt input image
  total_loss = all_loss[0]
  return tape.gradient(total_loss, cfg['init_image']), all_loss
```

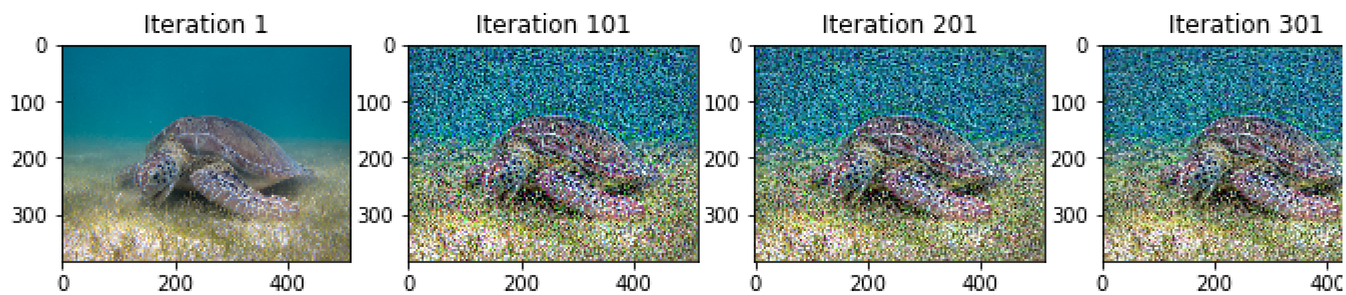
Optimization loop

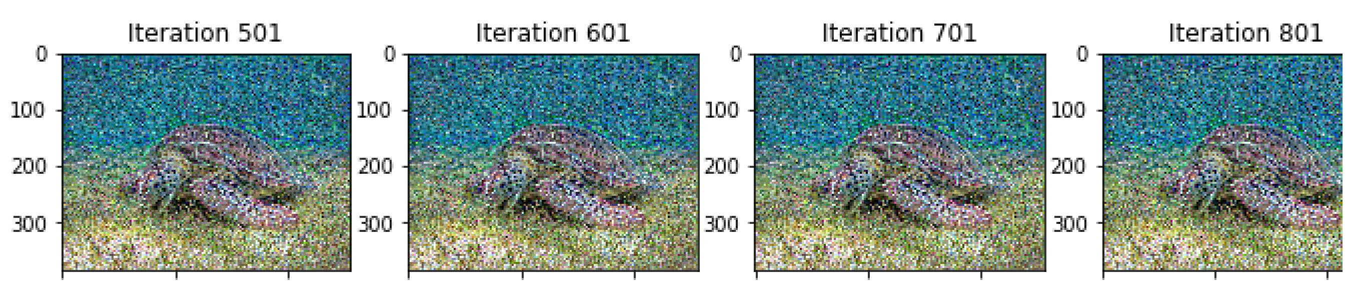
```
import IPython.display

def run_style_transfer(content_path,
                       style_path,
                       num_iterations=1000,
                       content_weight=1e3,
```

```
                      style_weight = 1e-2):
  display_num = 100
  # We don't need to (or want to) train any layers of our model, so we set their trainability
  # to false.
  model = get_model()
  for layer in model.layers:
    layer.trainable = False

  # Get the style and content feature representations (from our specified intermediate layers
  style_features, content_features = get_feature_representations(model, content_path, style_p
  gram_style_features = [gram_matrix(style_feature) for style_feature in style_features]

  # Set initial image
  init_image = load_and_process_img(content_path)
  init_image = tf.Variable(init_image, dtype=tf.float32)
  # Create our optimizer
  opt = tf.train.AdamOptimizer(learning_rate=10.0)

  # For displaying intermediate images
  iter_count = 1

  # Store our best result
  best_loss, best_img = float('inf'), None

  # Create a nice config
  loss_weights = (style_weight, content_weight)
  cfg = {
      'model': model,
      'loss_weights': loss_weights,
      'init_image': init_image,
      'gram_style_features': gram_style_features,
      'content_features': content_features
  }

  # For displaying
  plt.figure(figsize=(15, 15))
  num_rows = (num_iterations / display_num) // 5
  start_time = time.time()
  global_start = time.time()

  norm_means = np.array([103.939, 116.779, 123.68])
  min_vals = -norm_means
  max_vals = 255 - norm_means

  imgs = []

  for i in range(num_iterations):
    grads, all_loss = compute_grads(cfg)
    loss, style_score, content_score = all_loss
    #grads, _ = tf.clip_by_global_norm(grads, 5.0)
    opt.apply_gradients([(grads, init_image)])
    clipped = tf.clip_by_value(init_image, min_vals, max_vals)
```

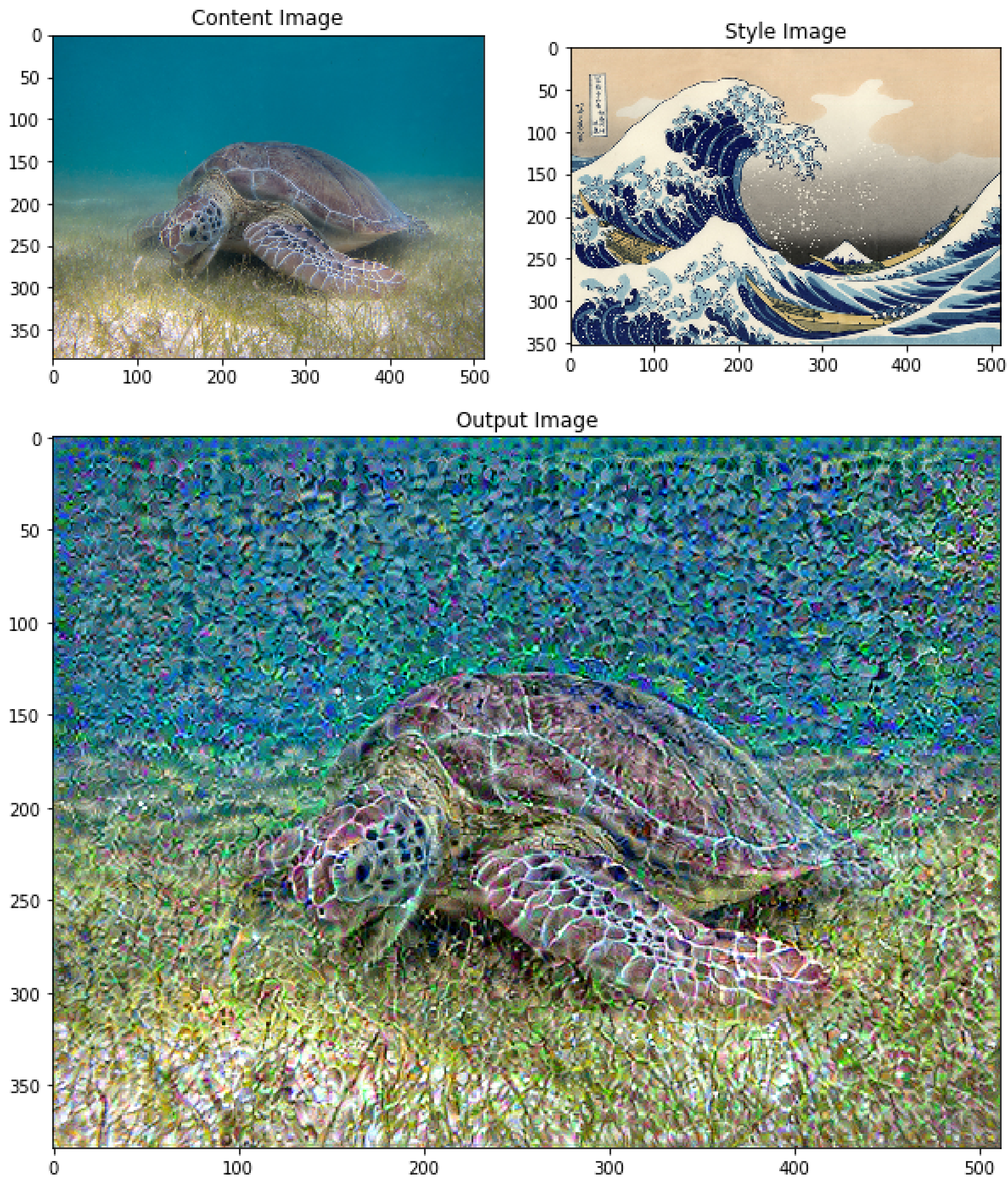
```
    init_image.assign(clipped)
    end_time = time.time()


    if loss < best_loss:
      # Update best loss and best image from total loss.
      best_loss = loss
      best_img = init_image


    if i % display_num == 0:

      # Use the .numpy() method to get the concrete numpy array
      plot_img = init_image.numpy()
      plot_img = deprocess_img(plot_img)
      imgs.append(plot_img)
      IPython.display.clear_output(wait=True)
      IPython.display.display_png(Image.fromarray(plot_img))
      print('Iteration: {}'.format(i))
      print('Total loss: {:.4e}, '
            'style loss: {:.4e}, '
            'content loss: {:.4e}, '
            'time: {:.4f}s'.format(loss, style_score, content_score, time.time() - start_time
      start_time = time.time()

      # Display intermediate images
      if iter_count > num_rows * 5: continue
      plt.subplot(num_rows, 5, iter_count)
      # Use the .numpy() method to get the concrete numpy array
      plot_img = init_image.numpy()
      plot_img = deprocess_img(plot_img)
      plt.imshow(plot_img)
      plt.title('Iteration {}'.format(i + 1))

      iter_count += 1
  print('Total time: {:.4f}s'.format(time.time() - global_start))

  return best_img, best_loss


best, best_loss = run_style_transfer(content_path,
                                     style_path, num_iterations=1001)
```

```
Iteration: 1000
Total loss: 6.6705e+03, style loss: 3.9069e-05, content loss: 6.6705e+03, time: 7.8961s
Total time: 78.9736s
```





```
def show_results(best_image, content_path, style_path, show_large_final=True):

  plt.figure(figsize=(10, 5))
  content = load_img(content_path)
  style = load_img(style_path)

  plt.subplot(1, 2, 1)
  imshow(content, 'Content Image')

  plt.subplot(1, 2, 2)
  imshow(style, 'Style Image')

  if show_large_final:
    plt.figure(figsize=(10, 10))

    best_image = best_image.numpy()
    best_image = deprocess_img(best_image)
    plt.imshow(best_image)
    plt.title('Output Image')
    plt.show()

show_results(best, content_path, style_path)
```




```
plt.imshow(deprocess_img(best)
```