```
import os
import sys
import scipy.io
import scipy.misc
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
from PIL import Image
import numpy as np
import tensorflow as tf

```

Neural Style Transfer merges two images, namely: a "content" image (C) and a "style" image (S), to create a "generated" image (G). The generated image G combines the "content" of the image C with the "style" of image S.

Neural Style Transfer (NST) uses a previously trained convolutional network, and builds on top of that. The idea of using a network trained on a different task and applying it to a new task is called transfer learning. Used VGG-19, a 19-layer version of the VGG network. This model has already been trained on the very large ImageNet database, and has learned to recognize a variety of low level features (at the shallower layers) and high level features (at the deeper layers).

```
vgg = tf.keras.applications.VGG19(include_top=False,
                                  input_shape=(img_size, img_size, 3),
                                  weights='imagenet')

vgg.trainable = False
```

```
<keras.src.engine.functional.Functional object at 0x7a111f397f10>
```

Building the Neural Style Transfer (NST) algorithm in three steps:

- 1) content cost function J_content(C,G)
- 2) style cost function J_style(S,G)
- 3) Total Cost J(G) = alpha *J_content(C,G) + beta *J_style(S,G)

$$J_{content}(C,G) = \frac{1}{4 \times n_H \times n_W \times n_C} \sum_{\text{all entries}} (a^{(C)} - a^{(G)})^2$$

$$J_{style}^{[l]}(S,G) = \frac{1}{4 \times {n_C}^2 \times (n_H \times n_W)^2} \sum_{i=1}^{n_C} \sum_{j=1}^{n_C} (G_{(gram)i,j}^{(S)} - G_{(gram)i,j}^{(G)})^2$$

- The shallower layers of a ConvNet tend to detect lower-level features such as edges and simple textures.
- The deeper layers tend to detect higher-level features such as more complex textures and object classes.

We need the "generated" image G to have similar content as the input image C. Suppose you have chosen some layer's activations to represent the content of an image.

- will get the most visually pleasing results if you choose a layer from somewhere in the middle of the network--neither too shallow nor too deep. This ensures that the network detects both higher-level and lower-level features.

forward propagate image C,

- Set the image C as the input to the pretrained VGG network, and run forward propagation.
- Let a^(C)(l) be the hidden layer activations in the layer l. This will be an n_H x n_W x n_C tensor.

forward propagate image G,

- Repeat this process with the image G: Set G as the input, and run forward propagation.
- Let a^(G)(l) be the corresponding hidden layer activation.

```
content_image = Image.open("/content/baby.jpg")
content_image

```

```
#function to compute Content Cost
def compute_content_cost(content_output, generated_output):
    """
    Computes the content cost

    Arguments:
    a_C -- tensor of dimension (1, n_H, n_W, n_C), hidden layer activations representing content of the image C
    a_G -- tensor of dimension (1, n_H, n_W, n_C), hidden layer activations representing content of the image G

    Returns:
    J_content -- scalar
    """
    a_C = content_output[-1]
    a_G = generated_output[-1]

    m, n_H, n_W, n_C = a_G.get_shape().as_list()

    # Reshape 'a_C' and 'a_G'
    a_C_unrolled = tf.reshape(a_C, shape=[m, n_H * n_W, n_C])
    a_G_unrolled = tf.reshape(a_G, shape=[m, n_H * n_W, n_C])

    J_content =  tf.reduce_sum(tf.square(a_C_unrolled - a_G_unrolled))/(4.0 * n_H * n_W * n_C)

    return J_content
```

```
example = Image.open("/content/Artwork.jpg")
example

```

Style Matrix/Gram matrix

- For the sake of clarity, in this assignment G_gram will be used to refer to the Gram matrix, and G to denote the generated image.

Computing Gram matrix G_gram by multiplying the "unrolled" filter matrix with its transpose:

G_gram = A_unrolled * A_unrolled^T

```
#function to Compute Gram Matrix
def gram_matrix(A):
    """
    Argument:
    A -- matrix of shape (n_C, n_H*n_W)
    Returns:
    GA -- Gram matrix of A, of shape (n_C, n_C)
    """
    GA = tf.matmul(A, tf.transpose(A))
    return GA
```

```
#function to compute layer style cost
def compute_layer_style_cost(a_S, a_G):
    """
    Arguments:
    a_S -- tensor of dimension (1, n_H, n_W, n_C), hidden layer activations representing style of the image S
    a_G -- tensor of dimension (1, n_H, n_W, n_C), hidden layer activations representing style of the image G

    Returns:
    J_style_layer
    """
    m, n_H, n_W, n_C = a_G.get_shape().as_list()

    # Reshape the tensors from (1, n_H, n_W, n_C) to (n_C, n_H * n_W)
    a_S = tf.transpose(tf.reshape(a_S, shape=[-1, n_C]))
    a_G = tf.transpose(tf.reshape(a_G, shape=[-1, n_C]))

    # Computing gram_matrices for both images S and G
    GS = gram_matrix(a_S)
    GG = gram_matrix(a_G)

    J_style_layer = tf.reduce_sum(tf.square(GS - GG))/(4.0 *(( n_H * n_W * n_C)**2))


    return J_style_layer
```

Style Weights

- better results if style costs from several different layers are merged.
- Each layer will be given weights, that reflect how much each layer will contribute to the style.

$$J_{style}(S,G) = \sum_{l} \lambda^{[l]} J^{[l]}_{style}(S,G)$$

listing the layer names:

```
for layer in vgg.layers:
    print(layer.name)
```

```
input_4
block1_conv1
block1_conv2
block1_pool
block2_conv1
block2_conv2
block2_pool
block3_conv1
block3_conv2
block3_conv3
block3_conv4
block3_pool
block4_conv1
block4_conv2
block4_conv3
block4_conv4
block4_pool
block5_conv1
block5_conv2
block5_conv3
block5_conv4
block5_pool
```

output of layer 'block5_conv4'.the content layer, which will represent the image.

```
vgg.get_layer('block5_conv4').output
```

```
<KerasTensor: shape=(None, 25, 25, 512) dtype=float32 (created by layer 'block5_conv4')>
```

layers to represent the style of the image and assigning style costs:

```
STYLE_LAYERS = [
    ('block1_conv1', 0.2),
    ('block2_conv1', 0.2),
    ('block3_conv1', 0.2),
    ('block4_conv1', 0.2),
    ('block5_conv1', 0.2)]
```

```
#function to compute combined style cost

def compute_style_cost(style_image_output, generated_image_output, STYLE_LAYERS=STYLE_LAYERS):
    """
    Computes the overall style cost from several layers

    Arguments:
    style_image_output -- our tensorflow model
    generated_image_output --
    STYLE_LAYERS -- A python list containing:
                        - the names of the layers we would like to extract style from
                        - a coefficient for each of them

    Returns:
    J_style
    """


    J_style = 0

    # Set a_S to be the hidden layer activation from the layer we have selected.
    # The last element of the array contains the content layer image
    a_S = style_image_output[:-1]

    # Set a_G to be the output of the hidden layers.
    # The last element of the list contains the content layer image
    a_G = generated_image_output[:-1]
    for i, weight in zip(range(len(a_S)), STYLE_LAYERS):
        # Compute style_cost for the current layer
        J_style_layer = compute_layer_style_cost(a_S[i], a_G[i])

        # Add weight * J_style_layer of this layer to overall style cost
        J_style += weight[1] * J_style_layer

    return J_style
```

Total_cost

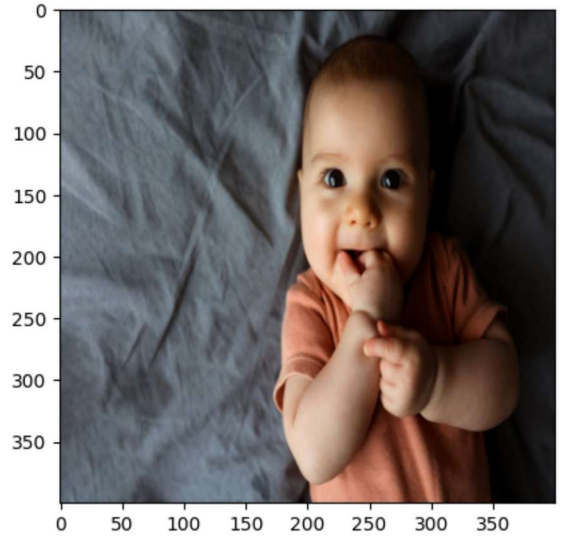
$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

```
#function to Compute Total Cost
@tf.function()
def total_cost(J_content, J_style, alpha = 10, beta = 40):
    """
    Arguments:
    J_content -- content cost coded above
    J_style -- style cost coded above
    alpha -- hyperparameter weighting the importance of the content cost
    beta -- hyperparameter weighting the importance of the style cost

    Returns:
    J -- total cost
    """
    J = alpha * J_content + beta * J_style

    return J
```

Load the Content Image and Resizing it to (400,400) and converting it to a tensor

```
content_image = np.array(Image.open("/content/baby.jpg").resize((400,400)))
content_image = tf.constant(np.reshape(content_image, ((1,) + content_image.shape)))

print(content_image.shape)
imshow(content_image[0])
plt.show()
```

```
(1, 400, 400, 3)
```



Load the Style Image and resizing and converting it to a tensor

```
style_image =  np.array(Image.open("/content/Artwork.jpg").resize((img_size, img_size)))
style_image = tf.constant(np.reshape(style_image, ((1,) + style_image.shape)))

print(style_image.shape)
imshow(style_image[0])
plt.show()
```

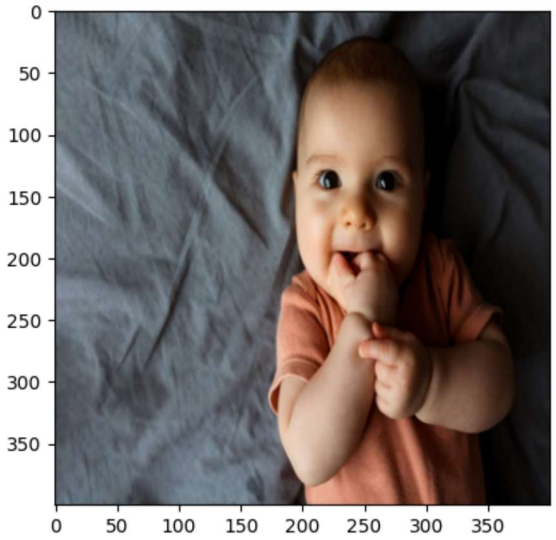
```
(1, 400, 400, 3)
```

Randomly initialize the image to be Generated

- initializing the "generated" image as content_image.

```
generated_image = tf.Variable(tf.image.convert_image_dtype(content_image, tf.float32))
# noise = tf.random.uniform(tf.shape(generated_image), -0.25, 0.25)
# generated_image = tf.add(generated_image, noise)
# generated_image = tf.clip_by_value(generated_image, clip_value_min=0.0, clip_value_max=1.0)

print(type(generated_image))
imshow(generated_image.numpy()[0])
plt.show()
```

```
<class 'tensorflow.python.ops.resource_variable_ops.ResourceVariable'>
```



Loading Pre-trained VGG19 Model

```
def get_layer_outputs(vgg, layer_names):
    """ Creates a vgg model that returns a list of intermediate output values."""
    outputs = [vgg.get_layer(layer[0]).output for layer in layer_names]

    model = tf.keras.Model([vgg.input], outputs)
    return model
```

defining the content layer and build the model.

```
content_layer = [('block5_conv4', 1)]

vgg_model_outputs = get_layer_outputs(vgg, STYLE_LAYERS + content_layer)
```

```
content_target = vgg_model_outputs(content_image)  # Content encoder
style_targets = vgg_model_outputs(style_image)     # Style encoder
```

Compute the Content image Encoding (a_C)

```
# Assign the content image to be the input of the VGG model.
# Set a_C to be the hidden layer activation from the layer we have selected
preprocessed_content =  tf.Variable(tf.image.convert_image_dtype(content_image, tf.float32))
a_C = vgg_model_outputs(preprocessed_content)
```

```
1
```

Compute the Style image Encoding (a_S)

The code below sets a_S to be the tensor giving the hidden layer activation for 'STYLE_LAYERS' using our style image.

```
# Assign the input of the model to be the "style" image
preprocessed_style =  tf.Variable(tf.image.convert_image_dtype(style_image, tf.float32))
a_S = vgg_model_outputs(preprocessed_style)
```

```
def clip_0_1(image):
    """
    Truncate all the pixels in the tensor to be between 0 and 1
    """
    return tf.clip_by_value(image, clip_value_min=0.0, clip_value_max=1.0)
```

```
def tensor_to_image(tensor):
    """
    Converts the given tensor into a PIL image
    """
    tensor = tensor * 255
    tensor = np.array(tensor, dtype=np.uint8)
    if np.ndim(tensor) > 3:
        assert tensor.shape[0] == 1
        tensor = tensor[0]
    return Image.fromarray(tensor)
```

Solving Optimization Problem

Implementing the train_step() function for transfer learning

- Using the Adam optimizer to minimize the total cost J.
- Using a learning rate of 0.01
- tf.GradientTape to update the image.
- tf.GradientTape():
    - Computing the encoding of the generated image using vgg_model_outputs. Assign the result to a_G.
    - Computing the total cost J, using the global variables a_C, a_S and the local a_G
    - Using 'alpha = 10' and 'beta = 40'.

```
print("TensorFlow version:", tf.__version__)
```

```
TensorFlow version: 2.14.0
```

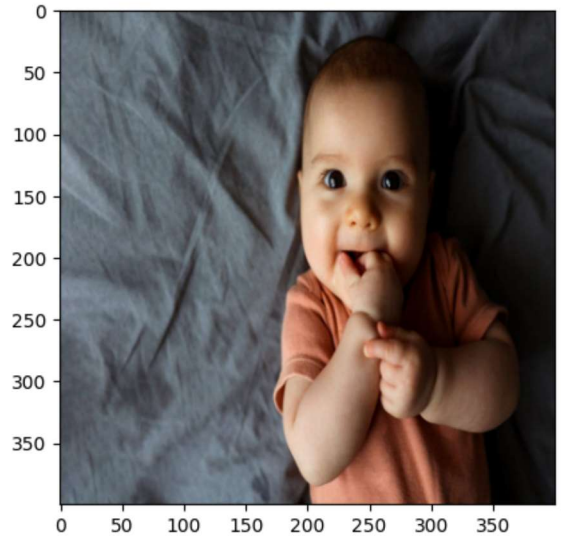
```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
@tf.function()
def train_step(generated_image, alpha = 10, beta = 40):
    # generated_image = tf.Variable(initial_value=generated_image, trainable=True)
    with tf.GradientTape() as tape:
        tape.watch(generated_image)
        # Computing a_G as the vgg_model_outputs for the current generated image
        a_G = vgg_model_outputs(generated_image)
        J_style = compute_style_cost(a_S, a_G)
        # print(J_style.shape)
        J_content = compute_content_cost(a_C, a_G)
        # print(J_content.shape)
        # Computing the total cost
        J = total_cost(J_content, J_style,alpha = alpha, beta = beta)
        print(type(J),J.shape)
        # print(J.shape)


```

```
    grad = tape.gradient(J, generated_image)
    print(type(grad),grad.shape)
    print(type(generated_image),generated_image.shape)
    optimizer.apply_gradients([(grad, generated_image)])
    generated_image.assign(clip_0_1(generated_image))
    # return J
```

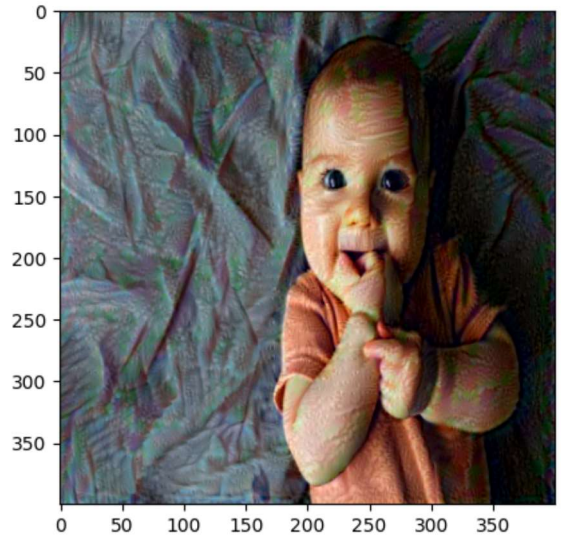
Update the image in every epoch- Training Step

```
# Showing the generated image at some epochs
epochs = 20001
for i in range(epochs):
    train_step(generated_image)
    if i % 500 == 0:
        print(f"Epoch {i} ")
        image = tensor_to_image(generated_image)
        imshow(image)
        plt.show()
```

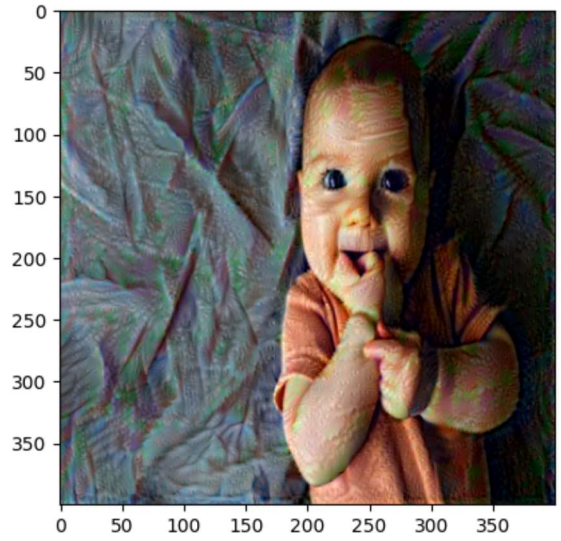
```
<class 'tensorflow.python.framework.ops.SymbolicTensor'> ()
<class 'tensorflow.python.framework.ops.SymbolicTensor'> (1, 400, 400, 3)
<class 'tensorflow.python.ops.resource_variable_ops.ResourceVariable'> (1, 400, 400, 3)
<class 'tensorflow.python.framework.ops.SymbolicTensor'> ()
<class 'tensorflow.python.framework.ops.SymbolicTensor'> (1, 400, 400, 3)
<class 'tensorflow.python.ops.resource_variable_ops.ResourceVariable'> (1, 400, 400, 3)
Epoch 0
```




```
Epoch 500
```




```
Epoch 1000
```




```
Epoch 1500
```