→ 1- Neural Style Transfer with 'Abstract Art' Painting Style

```
import numpy as np
from PIL import Image
import requests
from io import BytesIO
from keras import backend
from keras.models import Model
from keras.applications.vgg16 import VGG16
from scipy.optimize import fmin_l_bfgs_b
   Using TensorFlow backend.
ITERATIONS = 15
CHANNELS = 3
IMAGE SIZE = 500
IMAGE WIDTH = IMAGE SIZE
IMAGE HEIGHT = IMAGE SIZE
IMAGENET MEAN RGB VALUES = [123.68, 116.779, 103.939]
CONTENT WEIGHT = 0.05
STYLE WEIGHT = 5.5
TOTAL VARIATION WEIGHT = 0.995
TOTAL VARIATION LOSS FACTOR = 1.30
input image path = "input.png"
style image path = "style.png"
output image path = "output.png"
#Input visualization
input image = Image.open("/content/Csueastbay.jpg")
input image = input image.resize((IMAGE WIDTH, IMAGE HEIGHT))
input image.save(input image path)
input image
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# Style visualization
style_image = Image.open("/content/28.jpg")
style_image = style_image.resize((IMAGE_WIDTH, IMAGE_HEIGHT))
style_image.save(style_image_path)
style_image
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# Data normalization and reshaping from RGB to BGR
   input_image_array = np.asarray(input_image, dtype="float32")
   input_image_array = np.expand_dims(input_image_array, axis=0)
   input image array[:, :, :, 0] -= IMAGENET MEAN RGB VALUES[2]
   input_image_array[:, :, :, 1] -= IMAGENET_MEAN_RGB_VALUES[1]
   input_image_array[:, :, :, 2] -= IMAGENET_MEAN_RGB_VALUES[0]
   input image array = input image array[:, :, ::-1]
   style image array = np.asarray(style image, dtype="float32")
   style image array = np.expand dims(style image array, axis=0)
   style image array[:, :, :, 0] -= IMAGENET MEAN RGB VALUES[2]
   style image array[:, :, :, 1] -= IMAGENET MEAN RGB VALUES[1]
   style_image_array[:, :, :, 2] -= IMAGENET_MEAN_RGB_VALUES[0]
   style image array = style image array[:, :, ::-1]
   # Model
   input image = backend.variable(input image array)
   style image = backend.variable(style image array)
   combination image = backend.placeholder((1, IMAGE HEIGHT, IMAGE SIZE, 3))
   input tensor = backend.concatenate([input image, style image, combination image], axis=
   model = VGG16(input tensor=input tensor, include top=False)
https://colab.research.google.com/drive/1yK07XZs4AKOHOklkTXIWbJWbMao47Jsm#printMode=true
```

Downloading data from https://github.com/fchollet/deep-learning-models/releases/c def content loss(content, combination): return backend.sum(backend.square(combination - content)) layers = dict([(layer.name, layer.output) for layer in model.layers]) content layer = 'block2 conv2' layer features = layers[content_layer] content image features = layer features[0, :, :, :] combination_features = layer_features[2, :, :, :] loss = backend.variable(0.) loss =loss+ CONTENT WEIGHT * content loss(content image features, combination features) def gram_matrix(x): features = backend.batch flatten(backend.permute dimensions(x, (2, 0, 1))) gram = backend.dot(features, backend.transpose(features)) return gram def compute style loss(style, combination): style = gram matrix(style) combination = gram matrix(combination) size = IMAGE_HEIGHT * IMAGE_WIDTH return backend.sum(backend.square(style - combination)) / (4. * (CHANNELS ** 2) * style layers = ["block1 conv2", "block2 conv2", "block3 conv3", "block4 conv3", "bloc for layer name in style layers: layer features = layers[layer name] style features = layer features[1, :, :, :] combination features = layer features[2, :, :, :] style loss = compute style loss(style features, combination features) loss =loss+ (STYLE_WEIGHT / len(style_layers)) * style_loss def total variation loss(x): a = backend.square(x[:, :IMAGE_HEIGHT-1, :IMAGE_WIDTH-1, :] - x[:, 1:, :IMAGE_WID b = backend.square(x[:, :IMAGE HEIGHT-1, :IMAGE WIDTH-1, :] - x[:, :IMAGE HEIGHTreturn backend.sum(backend.pow(a + b, TOTAL VARIATION LOSS FACTOR)) loss =loss+ TOTAL VARIATION WEIGHT * total variation loss(combination image) outputs = [loss] outputs += backend.gradients(loss, combination_image) def evaluate loss and gradients(x): x = x.reshape((1, IMAGE HEIGHT, IMAGE WIDTH, CHANNELS))

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outs = backend.function([combination_image], outputs)([x])
    loss = outs[0]
    gradients = outs[1].flatten().astype("float64")
    return loss, gradients
class Evaluator:
    def loss(self, x):
        loss, gradients = evaluate_loss_and_gradients(x)
        self. gradients = gradients
        return loss
    def gradients(self, x):
        return self. gradients
evaluator = Evaluator()
outputs = [loss]
outputs += backend.gradients(loss, combination_image)
def evaluate loss and gradients(x):
    x = x.reshape((1, IMAGE_HEIGHT, IMAGE_WIDTH, CHANNELS))
    outs = backend.function([combination image], outputs)([x])
    loss = outs[0]
    gradients = outs[1].flatten().astype("float64")
    return loss, gradients
class Evaluator:
    def loss(self, x):
        loss, gradients = evaluate loss and gradients(x)
        self. gradients = gradients
        return loss
    def gradients(self, x):
        return self. gradients
evaluator = Evaluator()
x = np.random.uniform(0, 255, (1, IMAGE HEIGHT, IMAGE WIDTH, 3)) - 128.
for i in range(ITERATIONS):
    x, loss, info = fmin 1 bfgs b(evaluator.loss, x.flatten(), fprime=evaluator.gradi
    print("Iteration %d completed with loss %d" % (i, loss))
x = x.reshape((IMAGE_HEIGHT, IMAGE_WIDTH, CHANNELS))
x = x[:, :, ::-1]
x[:, :, 0] += IMAGENET MEAN RGB VALUES[2]
x[:, :, 1] += IMAGENET MEAN RGB VALUES[1]
x[:, :, 2] += IMAGENET MEAN RGB VALUES[0]
x = np.clip(x, 0, 255).astype("uint8")
```

```
output_image = Image.fromarray(x)
output_image.save(output_image_path)
output image
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Iteration 0 completed with loss 356573970432
Iteration 1 completed with loss 99040116736
Iteration 2 completed with loss 66125950976
Iteration 3 completed with loss 53006192640
Iteration 4 completed with loss 48568373248
Iteration 5 completed with loss 46689280000
Iteration 6 completed with loss 45687005184
Iteration 7 completed with loss 45101993984
Iteration 8 completed with loss 44735623168
Iteration 9 completed with loss 44479975424
Iteration 10 completed with loss 44279324672
Iteration 11 completed with loss 44121337856
Iteration 12 completed with loss 43996372992
Iteration 13 completed with loss 43894128640
Iteration 14 completed with loss 43807543296

