LAB 12-13 Patryk Kalinowski 80224

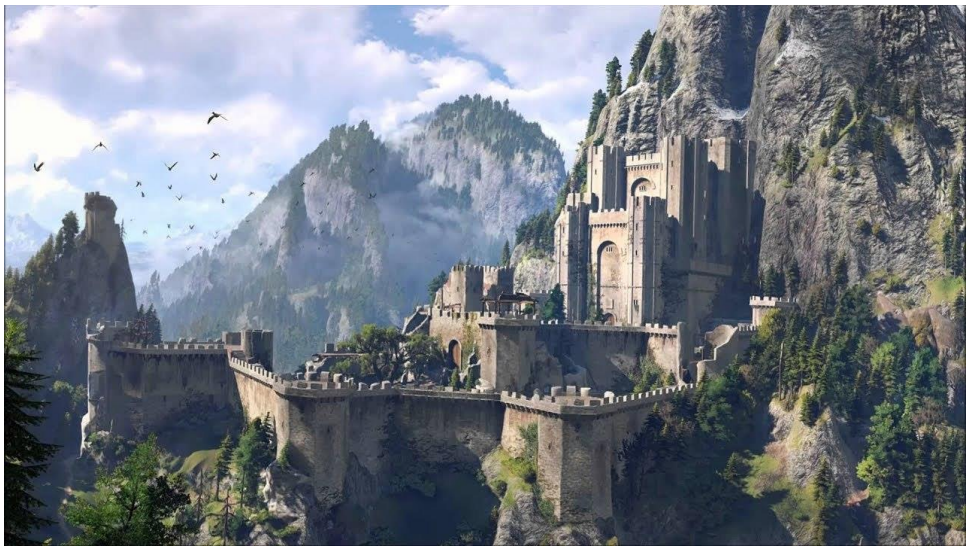
Źródło: https://keras.io/examples/generative/neural_style_transfer/

Importowanie odpowiednich ustawień wraz z załadowaniem obrazków

```
[11] import numpy as np
     import tensorflow as tf
     from tensorflow import keras
     from tensorflow.keras.applications import vgg19

     base_image_path = keras.utils.get_file("kaer.jpg", "https://www.purepc.pl/image/news/2018/12/14_wiedzmin_od_netfliksa_pierwsze_sceny_i_fotografie_kaer_morhen_0_b.jpg")
     style_reference_image_path = keras.utils.get_file(
         "scream.jpg", "https://upload.wikimedia.org/wikipedia/commons/thumb/c/c5/Edvard_Munch%2C_1893%2C_The_Scream%2C_oil%2C_tempera_and_pastel_on_cardboard%2C_91_x_73_cm%2C_National_Gallery_of_Nor
     )
     result_prefix = "paris_generated"

     # Weights of the different loss components
     total_variation_weight = 1e-6
     style_weight = 1e-6
     content_weight = 2.5e-8

     # Dimensions of the generated picture.
     width, height = keras.preprocessing.image.load_img(base_image_path).size
     img_nrows = 400
     img_ncols = int(width * img_nrows / height)
```

Wyświetlenie obrazów na ekran

```
[12] from IPython.display import Image, display

     display(Image(base_image_path))
     display(Image(style_reference_image_path))
```



Tworzenie narzędzia do wstępnego przetworzenia obrazu

```python
def preprocess_image(image_path):
    # Util function to open, resize and format pictures into appropriate tensors
    img = keras.preprocessing.image.load_img(
        image_path, target_size=(img_nrows, img_ncols)
    )
    img = keras.preprocessing.image.img_to_array(img)
    img = np.expand_dims(img, axis=0)
    img = vgg19.preprocess_input(img)
    return tf.convert_to_tensor(img)


def deprocess_image(x):
    # Util function to convert a tensor into a valid image
    x = x.reshape((img_nrows, img_ncols, 3))
    # Remove zero-center by mean pixel
    x[:, :, 0] += 103.939
    x[:, :, 1] += 116.779
    x[:, :, 2] += 123.68
    # 'BGR'->'RGB'
    x = x[:, :, ::-1]
    x = np.clip(x, 0, 255).astype("uint8")
    return x
```

Obliczanie straty transferu stylu, gdzie musimy zdefiniować 4 funkcje użytkowe:

- Gram_matrix - służy do obliczania utraty stylu,
- Style_loss – utrzymuje wygenerowany obraz blisko lokalnych tekstur obrazu odniesienia stylu,
- Content_loss – utrzymuje wysoką reprezentację wygenerowanego obrazu zbliżoną do obrazu bazowego,
- Total_varation_loss – utrata regularyzacji, która utrzymuje lokalnie spójny wygenerowany obraz.

```
[14] # The gram matrix of an image tensor (feature-wise outer product)


     def gram_matrix(x):
         x = tf.transpose(x, (2, 0, 1))
         features = tf.reshape(x, (tf.shape(x)[0], -1))
         gram = tf.matmul(features, tf.transpose(features))
         return gram


     # The "style loss" is designed to maintain
     # the style of the reference image in the generated image.
     # It is based on the gram matrices (which capture style) of
     # feature maps from the style reference image
     # and from the generated image


     def style_loss(style, combination):
         S = gram_matrix(style)
         C = gram_matrix(combination)
         channels = 3
         size = img_nrows * img_ncols
         return tf.reduce_sum(tf.square(S - C)) / (4.0 * (channels ** 2) * (size ** 2))


     # An auxiliary loss function
     # designed to maintain the "content" of the
     # base image in the generated image


     def content_loss(base, combination):
         return tf.reduce_sum(tf.square(combination - base))


     # The 3rd loss function, total variation loss,
     # designed to keep the generated image locally coherent


     def total_variation_loss(x):
         a = tf.square(
             x[:, : img_nrows - 1, : img_ncols - 1, :] - x[:, 1:, : img_ncols - 1, :]
         )
         b = tf.square(
             x[:, : img_nrows - 1, : img_ncols - 1, :] - x[:, : img_nrows - 1, 1:, :]
         )
         return tf.reduce_sum(tf.pow(a + b, 1.25))
```

Tworzymy model wyodrębnienia cech, który pobiera pośrednie aktywacje VGG19

```
[15] # Build a VGG19 model loaded with pre-trained ImageNet weights
     model = vgg19.VGG19(weights="imagenet", include_top=False)

     # Get the symbolic outputs of each "key" layer (we gave them unique names).
     outputs_dict = dict([(layer.name, layer.output) for layer in model.layers])

     # Set up a model that returns the activation values for every layer in
     # VGG19 (as a dict).
     feature_extractor = keras.Model(inputs=model.inputs, outputs=outputs_dict)
```

Kod obliczający utratę transferu stylu

```python
# List of layers to use for the style loss.
style_layer_names = [
    "block1_conv1",
    "block2_conv1",
    "block3_conv1",
    "block4_conv1",
    "block5_conv1",
]
# The layer to use for the content loss.
content_layer_name = "block5_conv2"


def compute_loss(combination_image, base_image, style_reference_image):
    input_tensor = tf.concat(
        [base_image, style_reference_image, combination_image], axis=0
    )
    features = feature_extractor(input_tensor)

    # Initialize the loss
    loss = tf.zeros(shape=())

    # Add content loss
    layer_features = features[content_layer_name]
    base_image_features = layer_features[0, :, :, :]
    combination_features = layer_features[2, :, :, :]
    loss = loss + content_weight * content_loss(
        base_image_features, combination_features
    )
    # Add style loss
    for layer_name in style_layer_names:
        layer_features = features[layer_name]
        style_reference_features = layer_features[1, :, :, :]
        combination_features = layer_features[2, :, :, :]
        sl = style_loss(style_reference_features, combination_features)
        loss += (style_weight / len(style_layer_names)) * sl

    # Add total variation loss
    loss += total_variation_weight * total_variation_loss(combination_image)
    return loss
```

Dodanie dekoratora (tf.function) do obliczania strat i gradientów

```python
@tf.function
def compute_loss_and_grads(combination_image, base_image, style_reference_image):
    with tf.GradientTape() as tape:
        loss = compute_loss(combination_image, base_image, style_reference_image)
    grads = tape.gradient(loss, combination_image)
    return loss, grads
```

Tworzenie pętli treningowej, ilość iteracji ustawiłem na 500, ze względu na oszczędność czasu (zgodnie ze źródłem powinno być 4000 iteracji)

Jesteśmy tutaj w stanie zmienić szybkość uczenia (decay_rate) oraz ilość korków (decay_steps)

```
[18] optimizer = keras.optimizers.SGD(
         keras.optimizers.schedules.ExponentialDecay(
             initial_learning_rate=100.0, decay_steps=100, decay_rate=0.96
         )
     )

     base_image = preprocess_image(base_image_path)
     style_reference_image = preprocess_image(style_reference_image_path)
     combination_image = tf.Variable(preprocess_image(base_image_path))

     iterations = 500
     for i in range(1, iterations + 1):
         loss, grads = compute_loss_and_grads(
             combination_image, base_image, style_reference_image
         )
         optimizer.apply_gradients([(grads, combination_image)])
         if i % 100 == 0:
             print("Iteration %d: loss=%.2f" % (i, loss))
             img = deprocess_image(combination_image.numpy())
             fname = result_prefix + "_at_iteration_%d.png" % i
             keras.preprocessing.image.save_img(fname, img)
```

Uruchomienie wygenerowanego obrazu

```
display(Image(result_prefix + "_at_iteration_500.png"))
```