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Exp	**No. 10 Application of Deep Learning Model on anApplicatio**

AIM : Transfer Image Style from one picture to other using GAN(General Adversarial Network)

Target:

Steps:

1. Obtain the actual or base image.
2. Obtain the style image.
3. Read the pixels of the base image.
4. Generate a statistical model of the pixels and their colour, depth andintensities.
5. Remove each pixel of the actual image and regenerate the same withthepixels of the style image.
6. The image matrix and pixel statistics helps the newer pixels of the styleimage to adjust in the exact places and do the needful.
7. Thus the final image will be obtained with the imposed style.

Importing the necessary packages:

```python
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import numpy as np
import os
from keras import backend as K
from keras.preprocessing.image import load_img, save_img, img_to_array
import matplotlib.pyplot as plt
from keras.applications import vgg19
from keras.models import Model
#from keras import optimizers
from scipy.optimize import fmin_l_bfgs_b
#from keras.applications.vgg19 import VGG19
#vgg19_weights = '../input/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5'
#vgg19 = VGG19(include_top = False, weights=vgg19_weights)
```

BASE IMAGE:

```python
def preprocess_image(image_path):
    from keras.applications import vgg19
    img = load_img(image_path, target_size=(img_nrows, img_ncols))
    img = img_to_array(img)
    img = np.expand_dims(img, axis=0)
    img = vgg19.preprocess_input(img)
    return img
```

```python
plt.figure()
plt.title("Base Image",fontsize=20)
img1 = load_img(ContentPath+'13.jpg')
plt.imshow(img1)
```

STYLE IMAGE:

```
plt.figure()
plt.title("Style Image",fontsize=20)
img1 = load_img(StylePath+'Pablo_Picasso/Pablo_Picasso_92.jpg')
plt.imshow(img1)
```


```
# get tensor representations of our images

base_image = K.variable(preprocess_image(base_image_path))
style_reference_image = K.variable(preprocess_image(style_image_path))
```

ALGORITHMS IN BETWEEN:

Building the VGG19 model

```
# build the VGG19 network with our 3 images as input
# the model will be loaded with pre-trained ImageNet weights
from keras.applications.vgg19 import VGG19
vgg19_weights = '../input/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5'
model = VGG19(input_tensor=input_tensor,
              include_top = False,
              weights=vgg19_weights)
#model = vgg19.VGG19(input_tensor=input_tensor,
#                    weights='imagenet', include_top=False)
print('Model loaded.')
```

Athough Vgg19 is basically used for Classification purpose, but here our objective is not to classify rather our objective is to transform a image, so we do not need all the layers of vgg19, we have specially excluded those layers which are used for classification.

```
# 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)
```

```
outputs_dict = dict([(layer.name, layer.output) for layer in model.layers])
print(outputs_dict['block5_conv2'])
```

The content Loss

Given a chosen content layer **l**, the content loss is defined as the Mean Squared Error between the feature map **F** of our content image **C** and the feature map **P** of our generated image **Y**.

$$\mathcal{L}_{content} = \frac{1}{2}\sum_{i,j}(F^l_{ij} - P^l_{ij})^2$$

```
# an auxiliary loss function
# designed to maintain the "content" of the
# base image in the generated image
def get_content_loss(base_content, target):
    return K.sum(K.square(target - base_content))
```

The Style Loss

To do this at first we need to, calculate the **Gram-matrix**(a matrix comprising of correlated features) for the tensors output by the style-layers. The Gram-matrix is essentially just a matrix of dot-products for the vectors of the feature activations of a style-layer.

If an entry in the Gram-matrix has a value close to zero then it means the two features in the given layer do not activate simultaneously for the given style-image. And vice-versa, if an entry in the Gram-matrix has a large value, then it means the two features do activate simultaneously for the given style-image. We will then try and create a mixed-image that replicates this activation pattern of the style-image. If the feature map is a matrix **F**, then each entry in the Gram matrix **G** can be given by:

$$G_{ij} = \sum_k F_{ik}F_{jk}$$

The loss function for style is quite similar to out content loss, except that we calculate the Mean Squared Error for the Gram-matrices instead of the raw tensor-outputs from the layers.

$$\mathcal{L}_{style} = \frac{1}{2}\sum_{l=0}^{L}(G^l_{ij} - A^l_{ij})^2$$

```
import tensorflow as tf
# the gram matrix of an image tensor (feature-wise outer product)
def gram_matrix(input_tensor):
    assert K.ndim(input_tensor)==3
    #if K.image_data_format() == 'channels_first':
    #    features = K.batch_flatten(input_tensor)
    #else:
    #    features = K.batch_flatten(K.permute_dimensions(input_tensor,(2,0,1)))
    #gram = K.dot(features, K.transpose(features))
    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(style, combination):
    assert K.ndim(style) == 3
    assert K.ndim(combination) == 3
    S = gram_matrix(style)
    C = gram_matrix(combination)
    channels = 3
    size = img_nrows*img_ncols
    return K.sum(K.square(S - C))#/(4.0 * (channels ** 2) * (size ** 2))
```

Calculation of gradient with respect to loss..

```
# get the gradients of the generated image wrt the loss
grads = K.gradients(loss, combination_image)
grads
```

```
outputs = [loss]
if isinstance(grads, (list,tuple)):
    outputs += grads
else:
    outputs.append(grads)
f_outputs = K.function([combination_image], outputs)
f_outputs
```

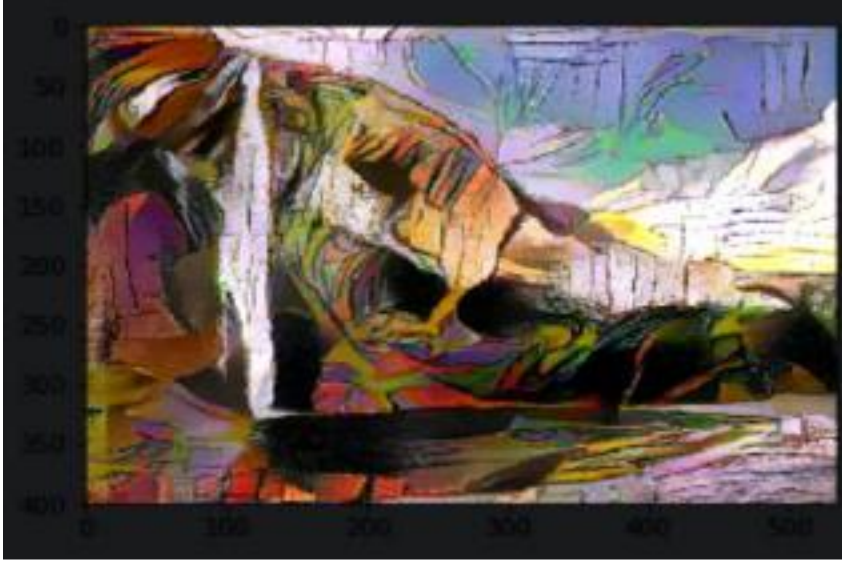
```
class Evaluator(object):

    def __init__(self):
        self.loss_value = None
        self.grads_values = None

    def loss(self, x):
        assert self.loss_value is None
        loss_value, grad_values = eval_loss_and_grads(x)
        self.loss_value = loss_value
        self.grad_values = grad_values
        return self.loss_value

    def grads(self, x):
        assert self.loss_value is not None
        grad_values = np.copy(self.grad_values)
        self.loss_value = None
        self.grad_values = None
        return grad_values
```

```
evaluator = Evaluator()
```

```
iterations=400
# Store our best result
best_loss, best_img = float('inf'), None
for i in range(iterations):
    print('Start of iteration', i)
    x_opt, min_val, info= fmin_l_bfgs_b(evaluator.loss,
                                        x_opt.flatten(),
                                        fprime=evaluator.grads,
                                        maxfun=20,
                                        disp=True,
                                       )
    print('Current loss value:', min_val)
    if min_val < best_loss:
        # Update best loss and best image from total loss.
        best_loss = min_val
        best_img = x_opt.copy()
```

FINAL IMAGE:

```
# save current generated image
imgx = deprocess_image(best_img.copy())
plt.imshow(imgx)
```



Conclusion:

The base image is thus style transferred using the style image and hencetheresultant image is obtained.

[PS: This is to a large extent similar to the image to sketch generation, but here the pen style and colours are also considered]