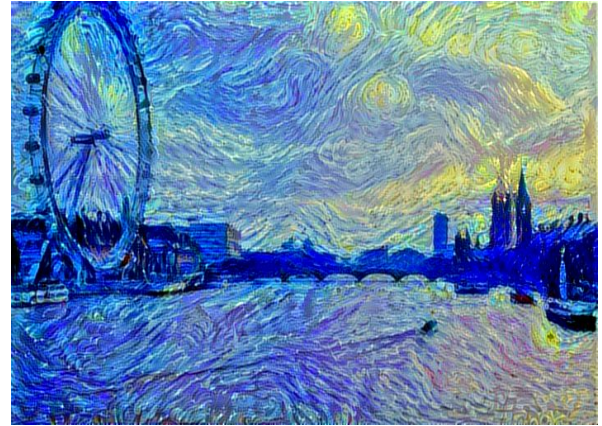


Image Processing 2021

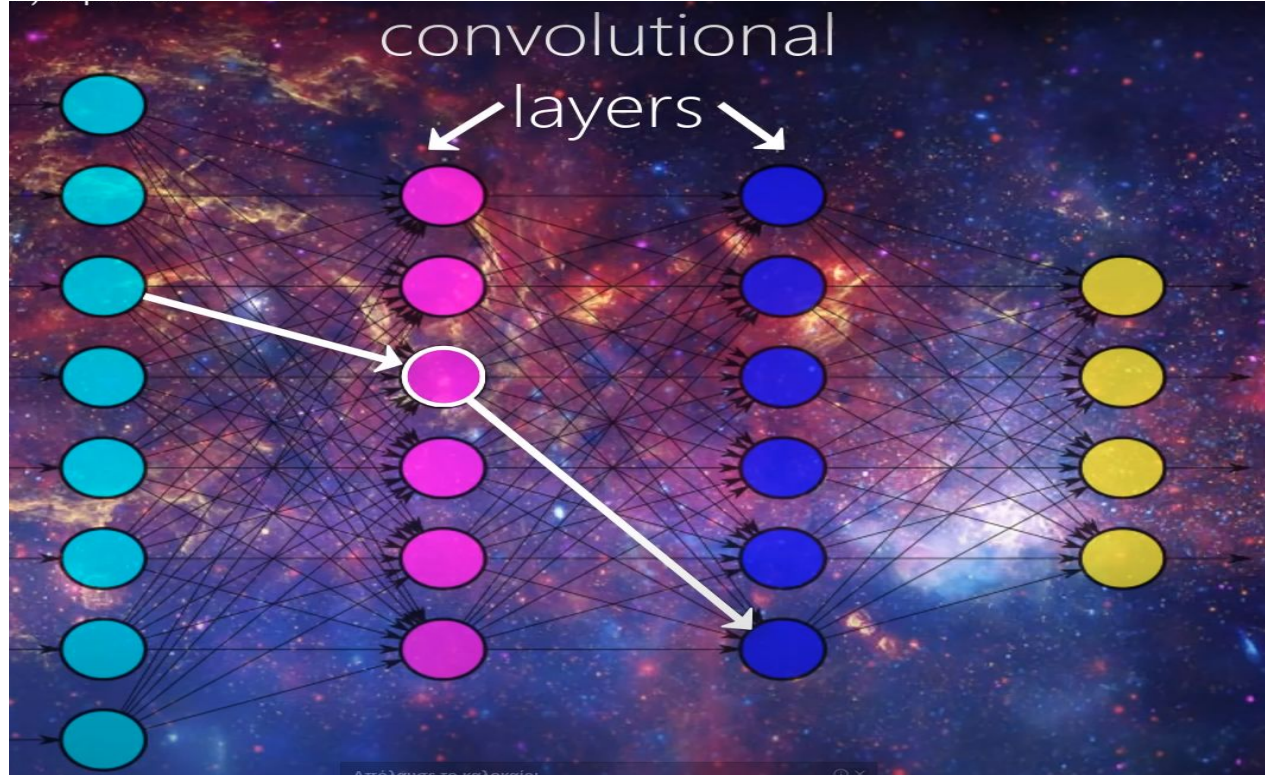
Stefanos Baklavas

Image Processing with Convolutional Neural Networks (CNN's) and using VGG19 to implement Van Gogh style on any picture

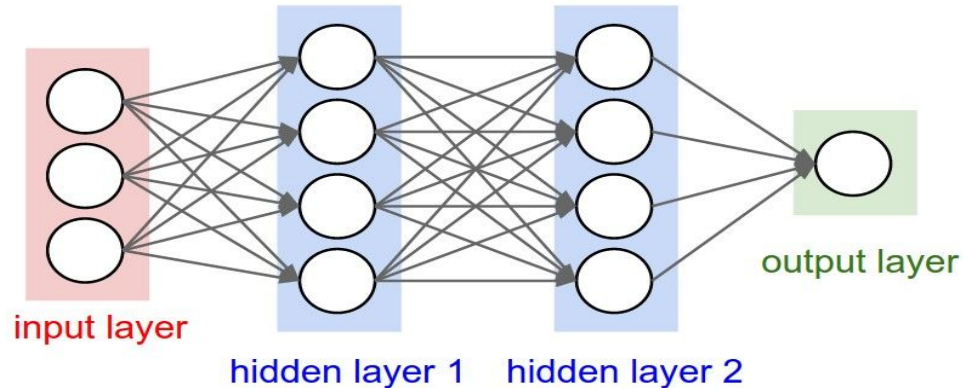
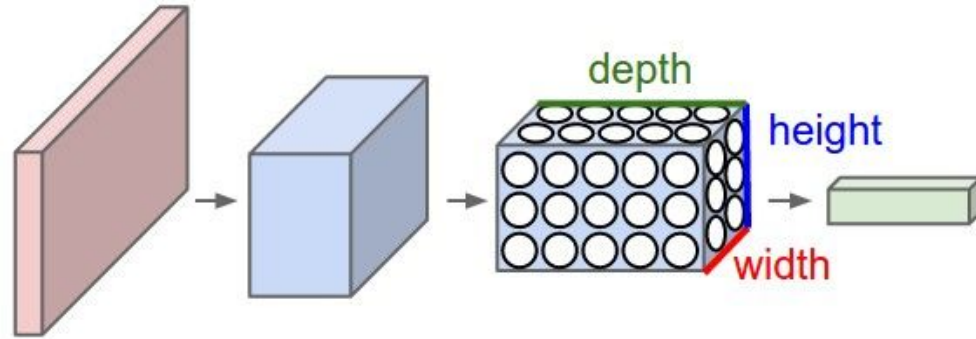


Why CNN's for Image Processing?

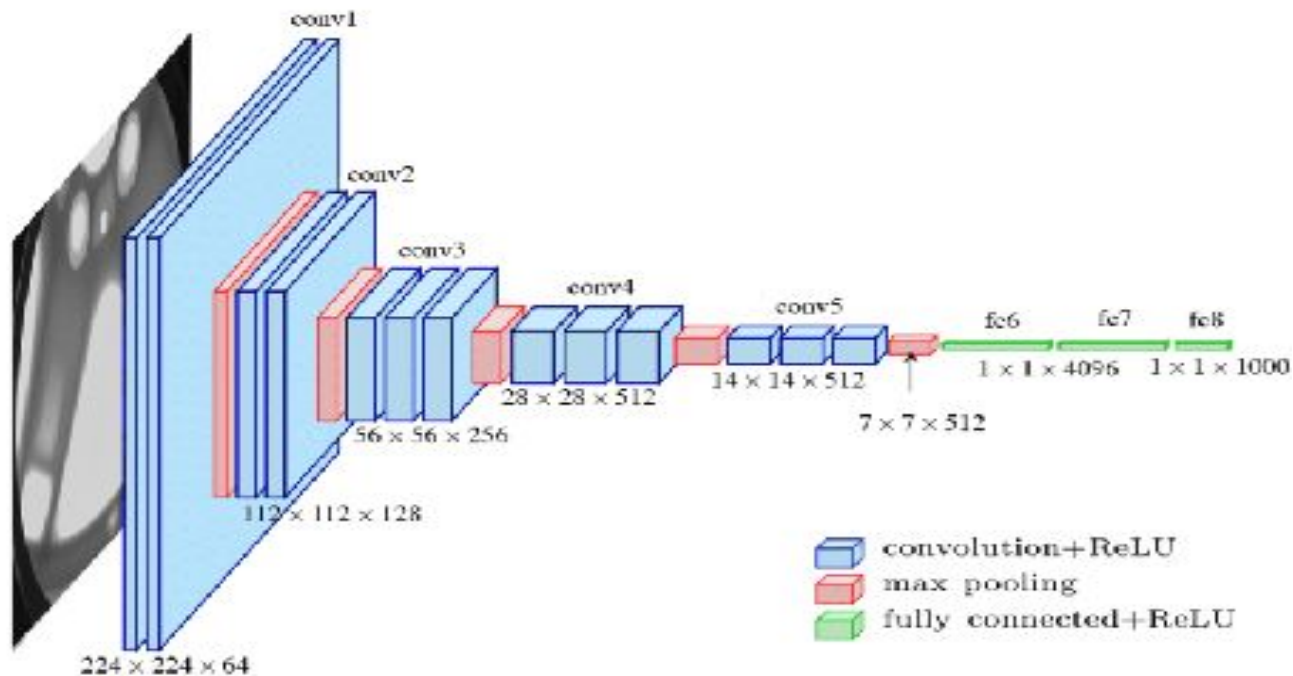
- CNN's are very good in detecting patterns and making a sense of them. That's what makes them useful for image analysis.
- The thing that makes them different from other Neural Networks is that their hidden layers are convolutional layers.
- They also include other types of layers (max pooling,relu etc.) which are used as filters for activation and input passing.
- A Convolutional layer:
 1. Receives input
 2. Transforms the input
 3. Outputs the transform to the next layer.



CNN vs Traditional Neural Network

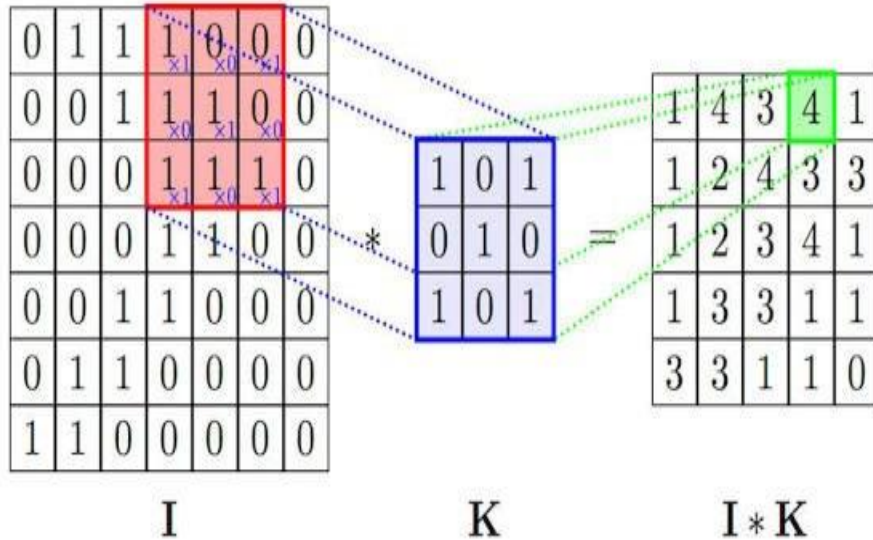


The VGG19 Architecture

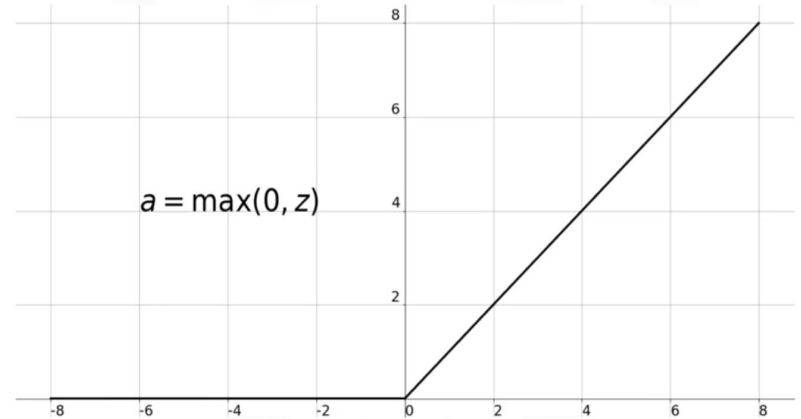


Types of Layers

1. Convolutional + ReLu

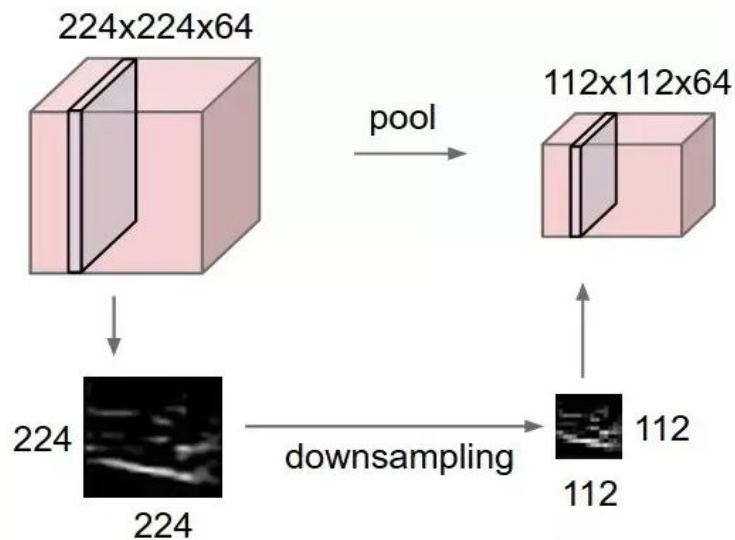
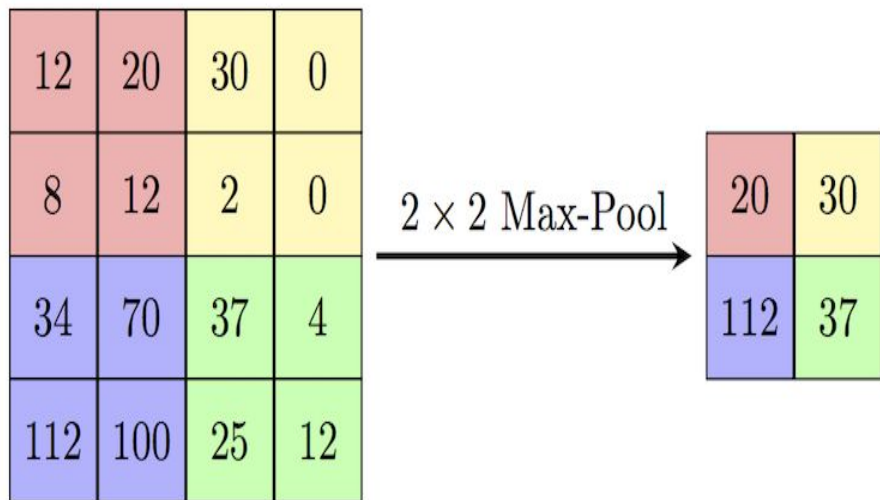


ReLU Function



Types of Layers

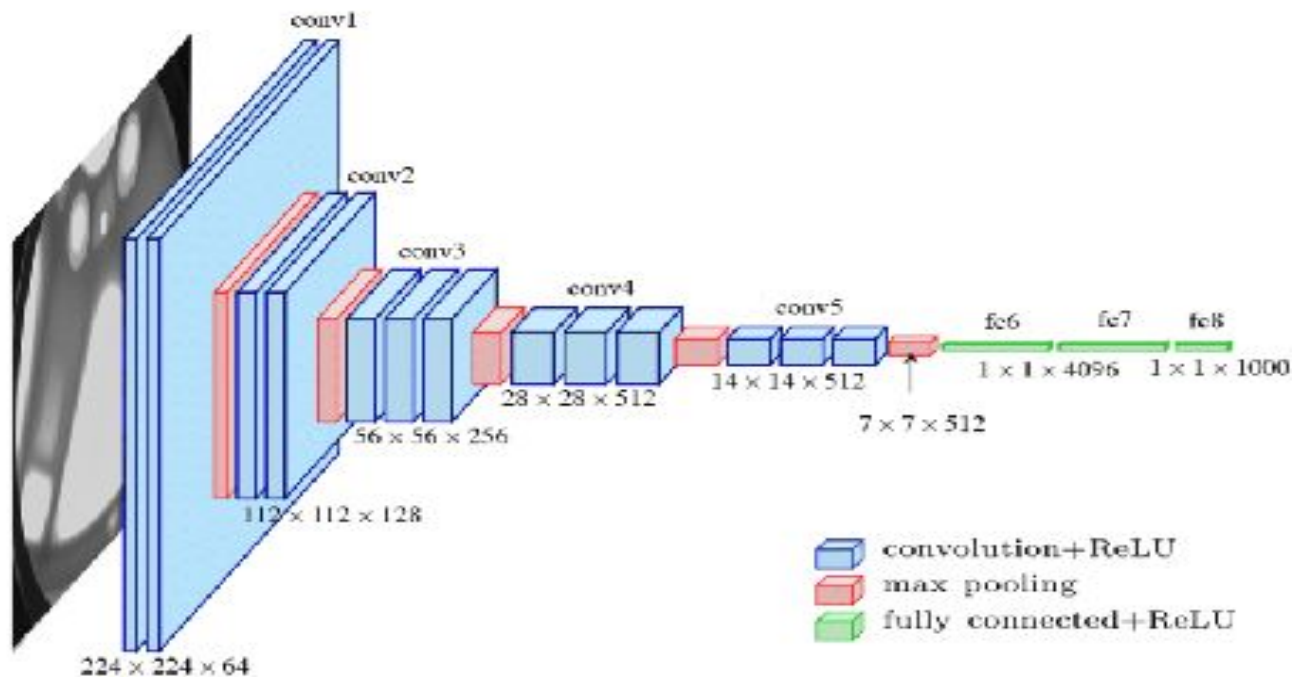
2. Max Pooling



Types of Layers

In this implementation we do not use the final fully connected layers and we receive our output from layer conv5_2.

The VGG19 Architecture part2:



VGG19 characteristics:

- 5 layers (16 convolutional layers, 3 Fully connected layer, 5 MaxPool layers and 1 Softmax layer). In this project we use the first 16 layers.
- Pre trained on millions of samples and has been developed by Oxford University
- The input image to the network should be a $224 \times 224 \times 3$ preprocessed RGB image .During preprocessing we subtract the mean RGB value from each pixel.
- The convolutional filter are 3×3 with stride = 1 and padding = 1.
- Max pooling is performed over a 2×2 pixel window with stride = 2.
- Fully connected layers are not used in this implementation (the final layer outputs the probabilities of each of the 1,000 output categories. That doesn't concern us)

Painting like Van Gogh (content)

To extract content from a picture we use the following algorithm:

1. Run the content image through the model and get the activation output of layer conv5_2 (P5_2)
2. Run the (initially random) target image x through the model and get the conv5_2 layer output (F5_2)
3. Calculate the content cost between the two outputs.

$$\sum (P_{5_2} - F_{5_2})^2.$$

4. Tweak the target image by back propagating the error back to target image and use that as a basis for out tweaking
5. Repeat 2-4 until satisfied.

Painting like Van Gogh (style)

The process is the same as before but instead of passing the output of each layer directly to the squared error function we first apply a function called Gram matrix.

The Gram matrix computes the correlations between the different filter responses.

G_{ij}^l is the inner product between the vectorised feature map i and j in layer l .

Style Loss (one layer)

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l.$$

Style layer
H = 2
W = 2
F = 2

Gram matrix

$$A = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} \quad a_1 \quad \begin{bmatrix} 5 \\ 6 \\ 7 \\ 8 \end{bmatrix} \quad a_2$$
$$G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \\ a_2 \cdot a_1 & a_2 \cdot a_2 \end{bmatrix} = A^T A$$

Painting like Van Gogh (content + style)

To paint both style *and* content we follow a similar process of iterative tweaking but employing a joint cost function that contains both content and style loss:

$$\text{total cost} = \text{content cost} + \text{style cost}$$

The optimization algorithm used in each iteration is the L-BFGS which is a popular algorithm for parameter estimation in machine learning. Its target is to minimize $f(x)$ over unconstrained values of the real-vector x where f is a differentiable scalar function.

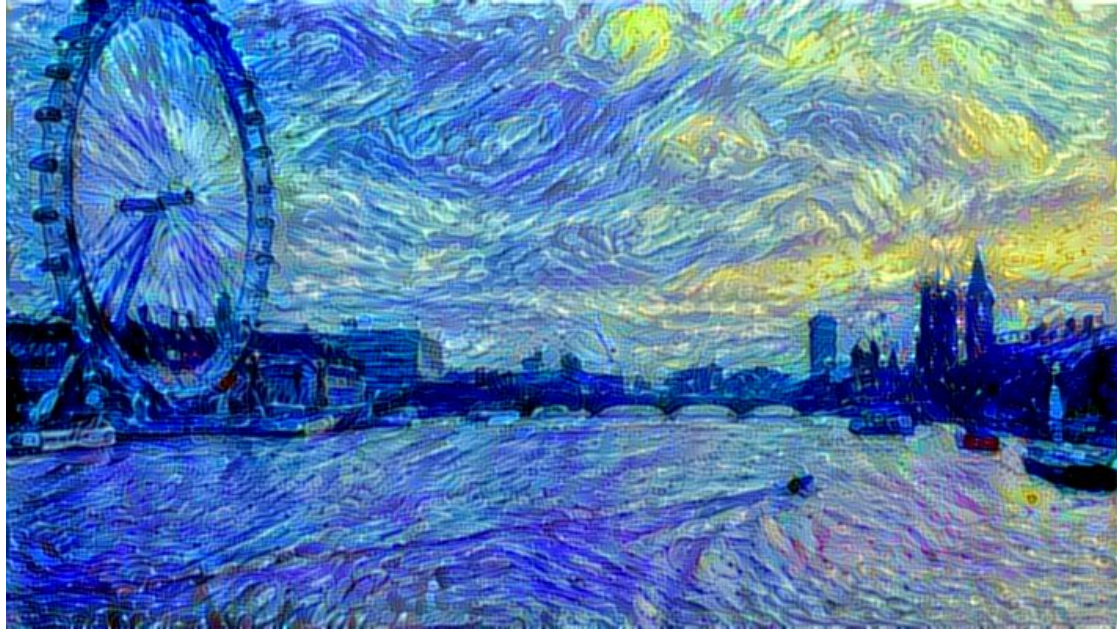
Comparing Results part 1:

content(5_2) - style(1_1,2_1,3_1,4_1,5_1)



Comparing Results part 2:

content(5_2) - style(1_2,2_2,3_2,4_2,5_2)



Comparing Results part 3:

content(5_2) - style(1_2,2_2,3_3,4_3,5_4)



Comparing Results part 4:

content(5_2) - style(1_1)



Comparing Results part 5:

content(5_2) - style(2_1)



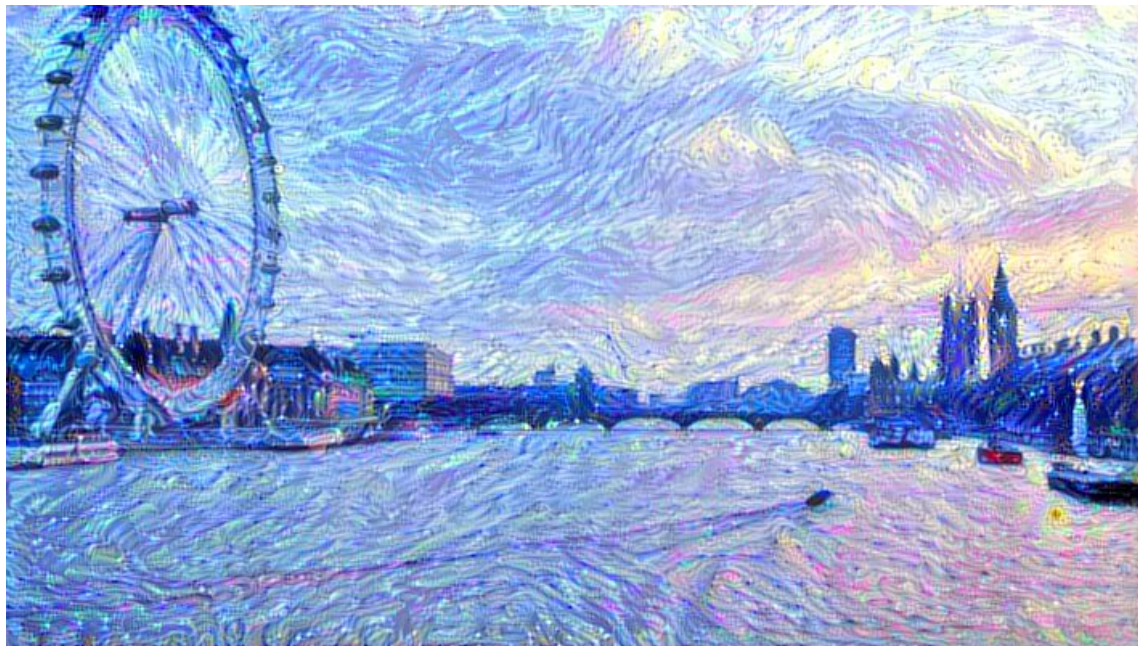
Comparing Results part 6:

content(5_2) - style(3_1)



Comparing Results part 7:

content(5_2) - style(4_1)



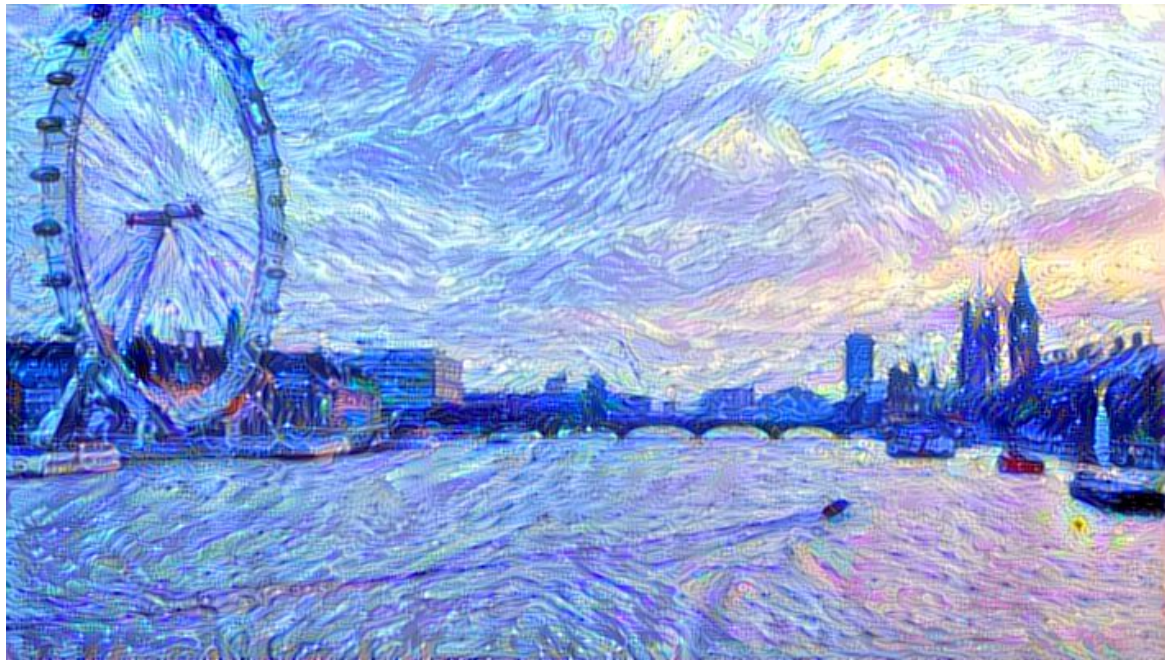
Comparing Results part 8:

content(5_2) - style(5_1)



Comparing Results part 9:

content(5_2) - style(3_1,4_1)



Comparing Results part 10:

content(5_2) - style(2_1)



Comparing Results part 11:

content(5_2) - style(1_1,1_2,,2_1,2_2,3_1,3_2,4_1,4_2,5_1,5_2,5_3)



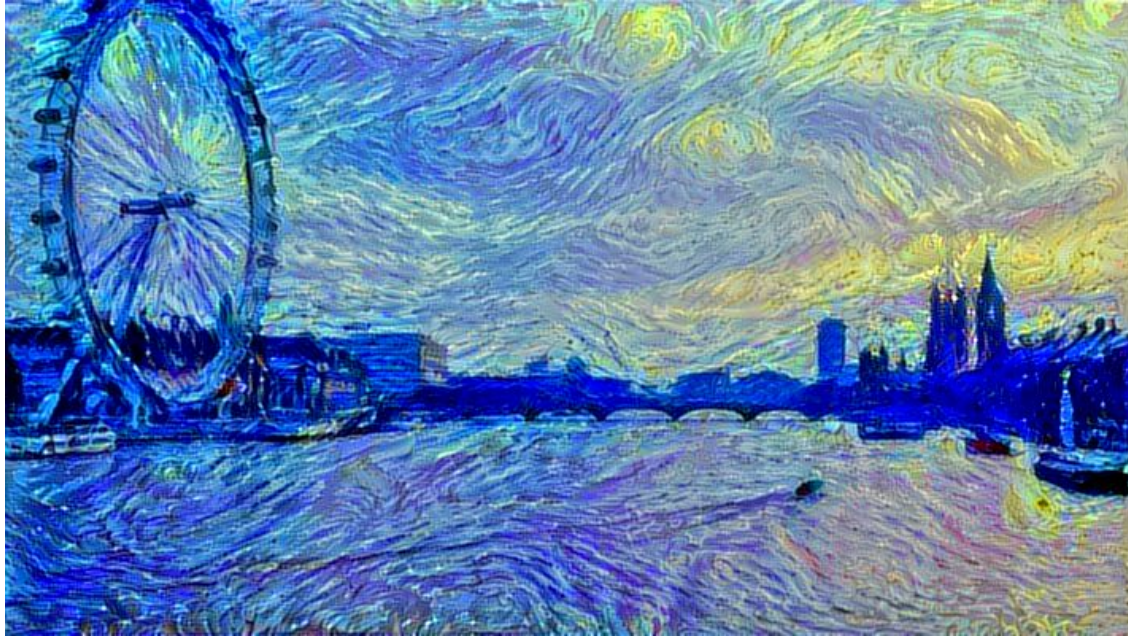
Comparing Results part 12:

content(5_2) - style(ολα τα layers)



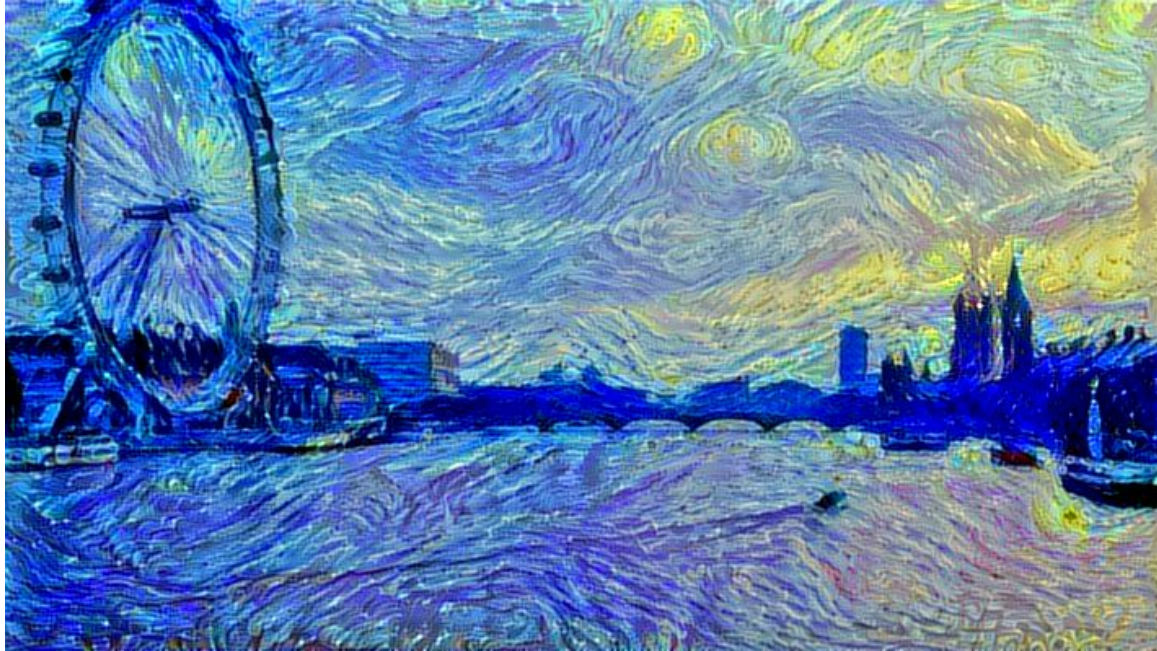
Comparing Results part 13:

content(5_2) - style(all layers) and weight_style = 5, weight_content = 5



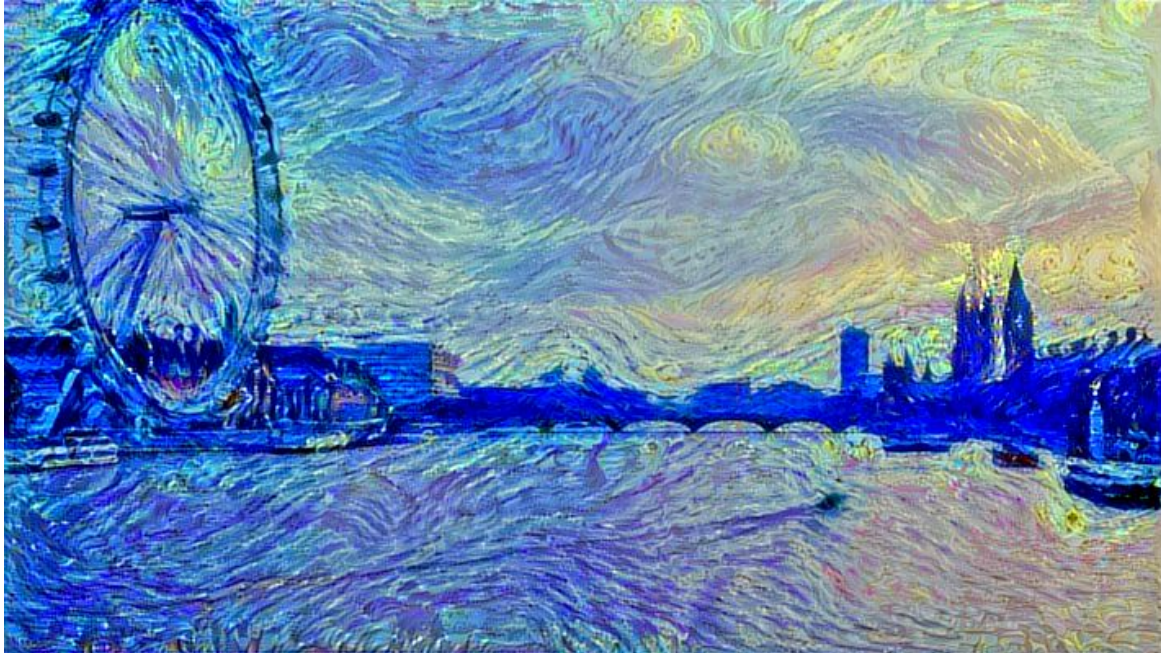
Comparing Results part 14:

content(5_2) - style(all layers) and weight_style = 5, weight_content = 2



Comparing Results part 15:

content(5_2) - style(all layers) and weight_style = 8, weight_content = 2



Comparing Results part 16:

content(5_2) - style(all layers) and weight_style = 2, weight_content = 8

