Copyright Notice

Style Transfer

Style Image

Wassily Kandinsky (wikipedia)
https://upload.wikimedia.org/wikipedia/commons/b/b4/Vassily_Kandinsky%2C_1913_-_Composition_7.jpg

Content Image

https://cdn.pixabay.com/photo/2017/02/28/23/00/swan-2107052_1280.jpg

Stylized Image

Approaches to Style Transfer

1. Supervised Learning.
2. Neural Style Transfer
3. Fast Neural Style Transfer

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- Pairs: original & stylized image.
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A Neural Algorithm of Artistic Style

Leon Gatys
Alexander Ecker
Matthias Bethge

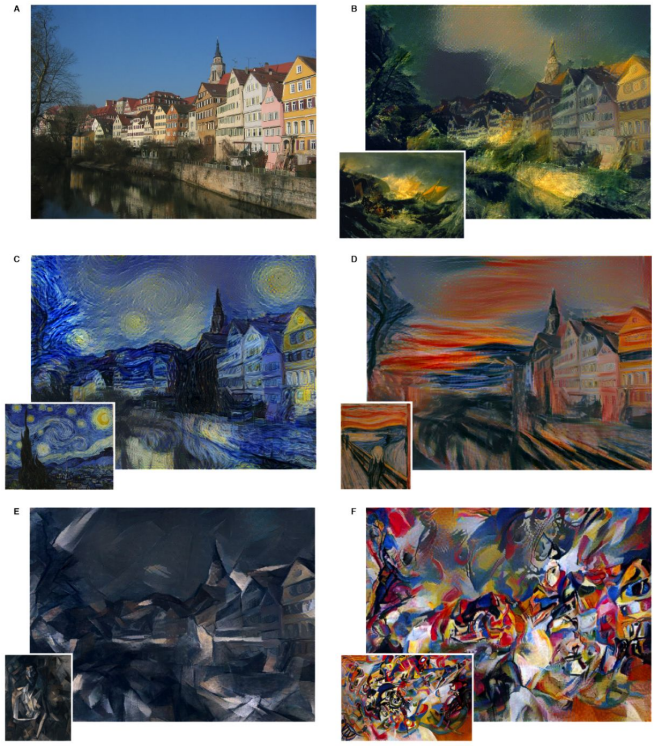
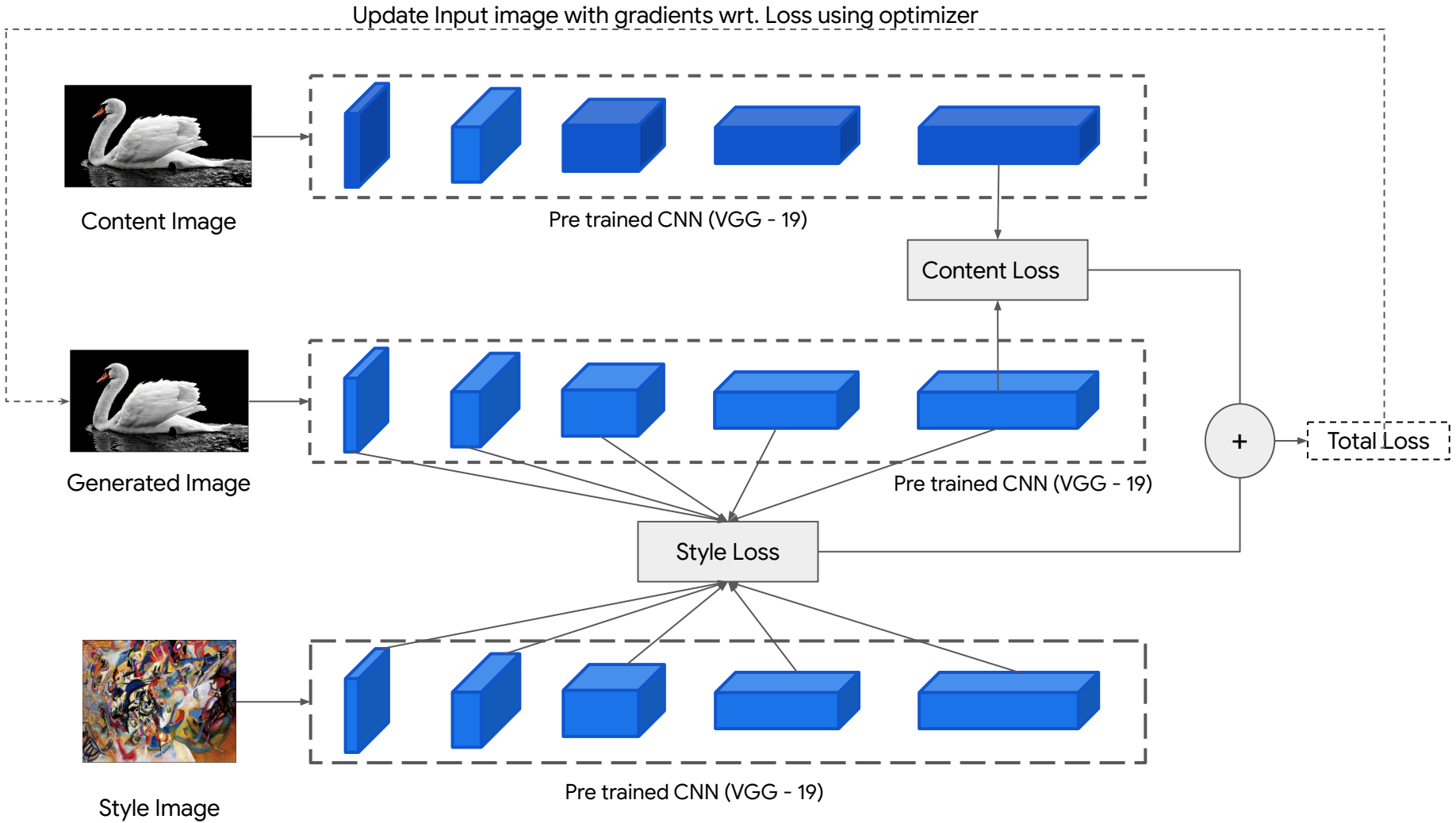


Figure 2: Images that combine the content of a photograph with the style of several well-known artworks. The images were created by finding an image that simultaneously matches the content representation of the photograph and the style representation of the artwork (see Methods). The

https://arxiv.org/abs/1508.06576


Update Input image with gradients wrt. Loss using optimizer
Content Image
Pre trained CNN (VGG - 19)
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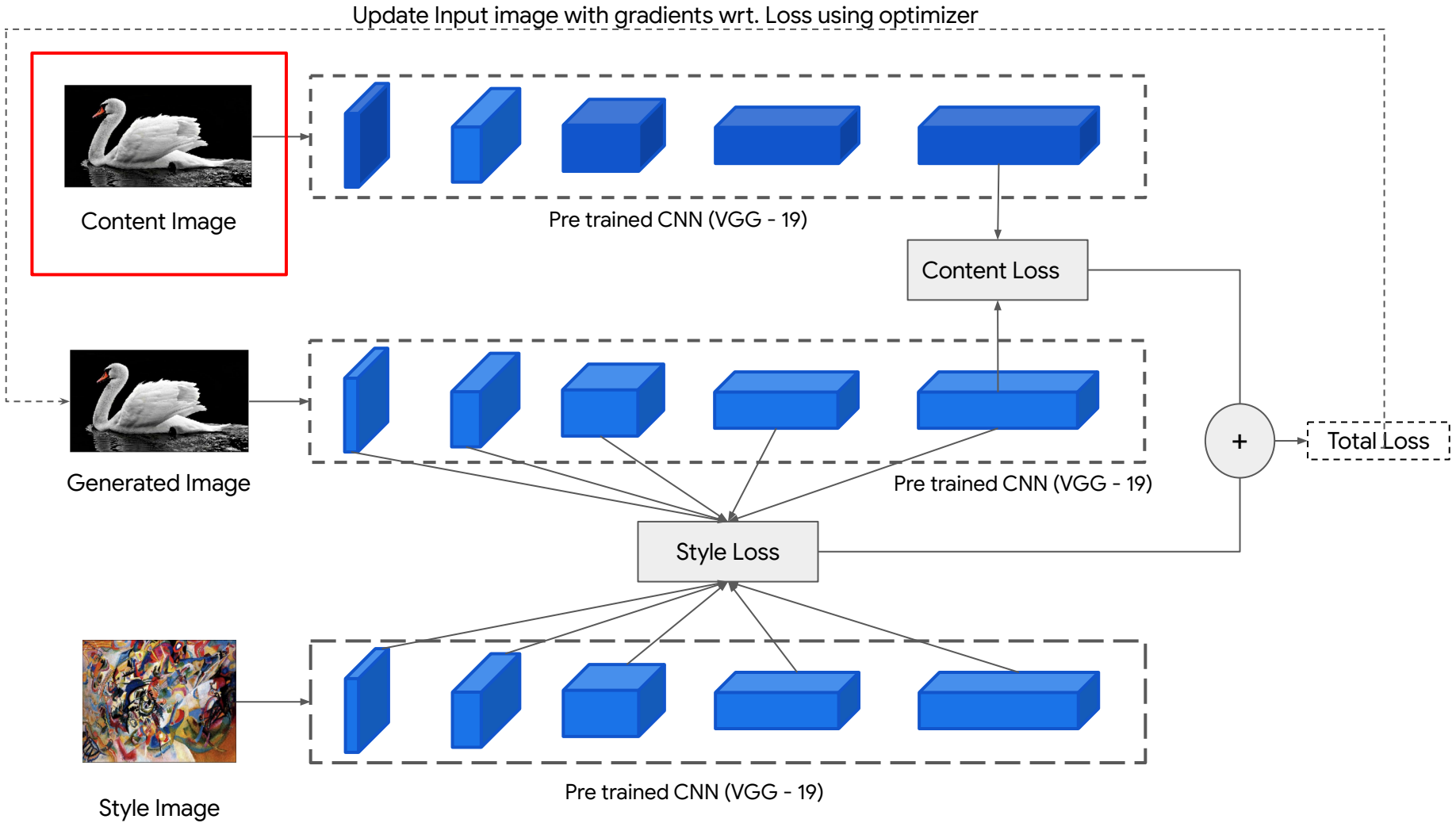
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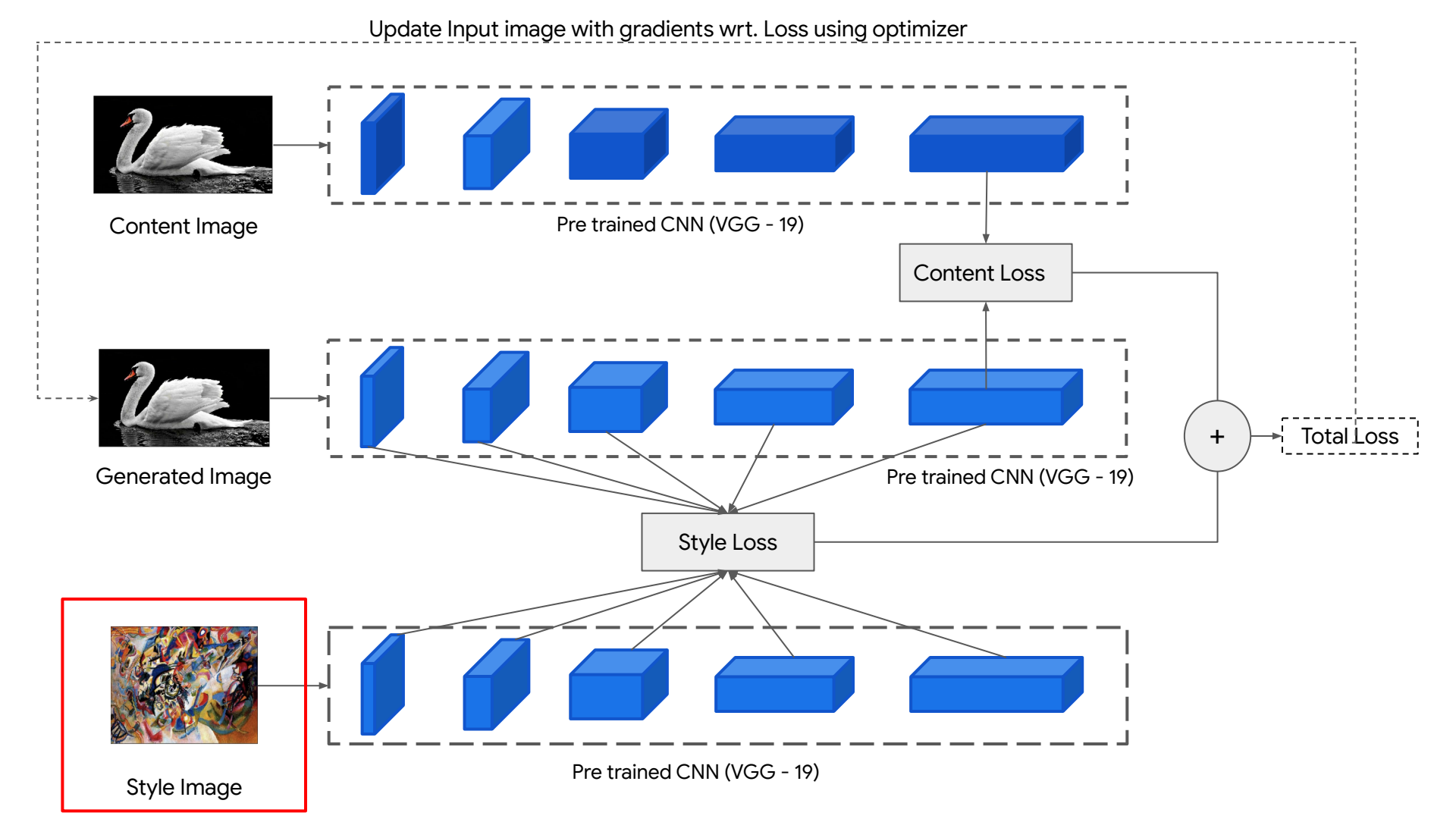
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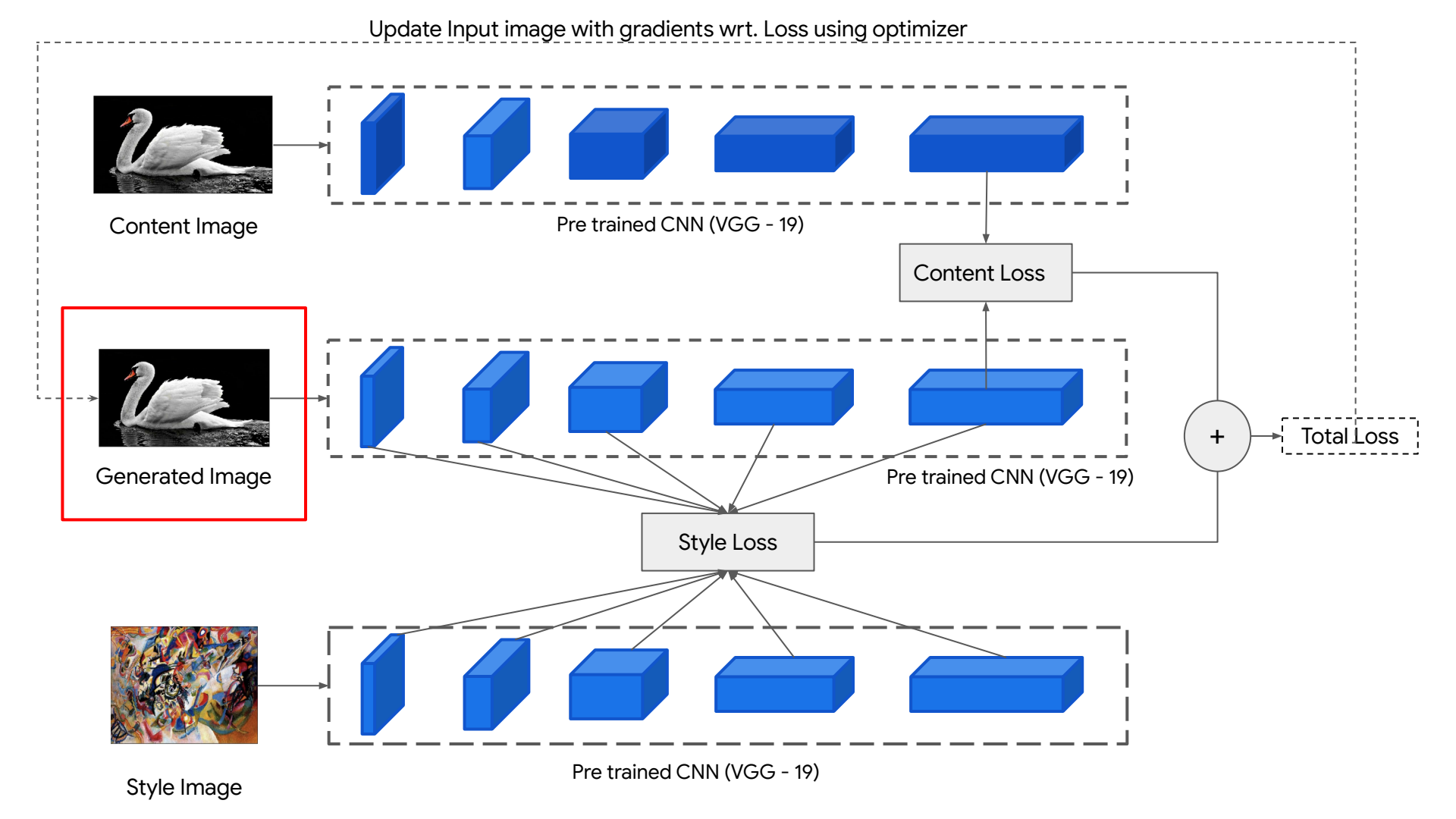
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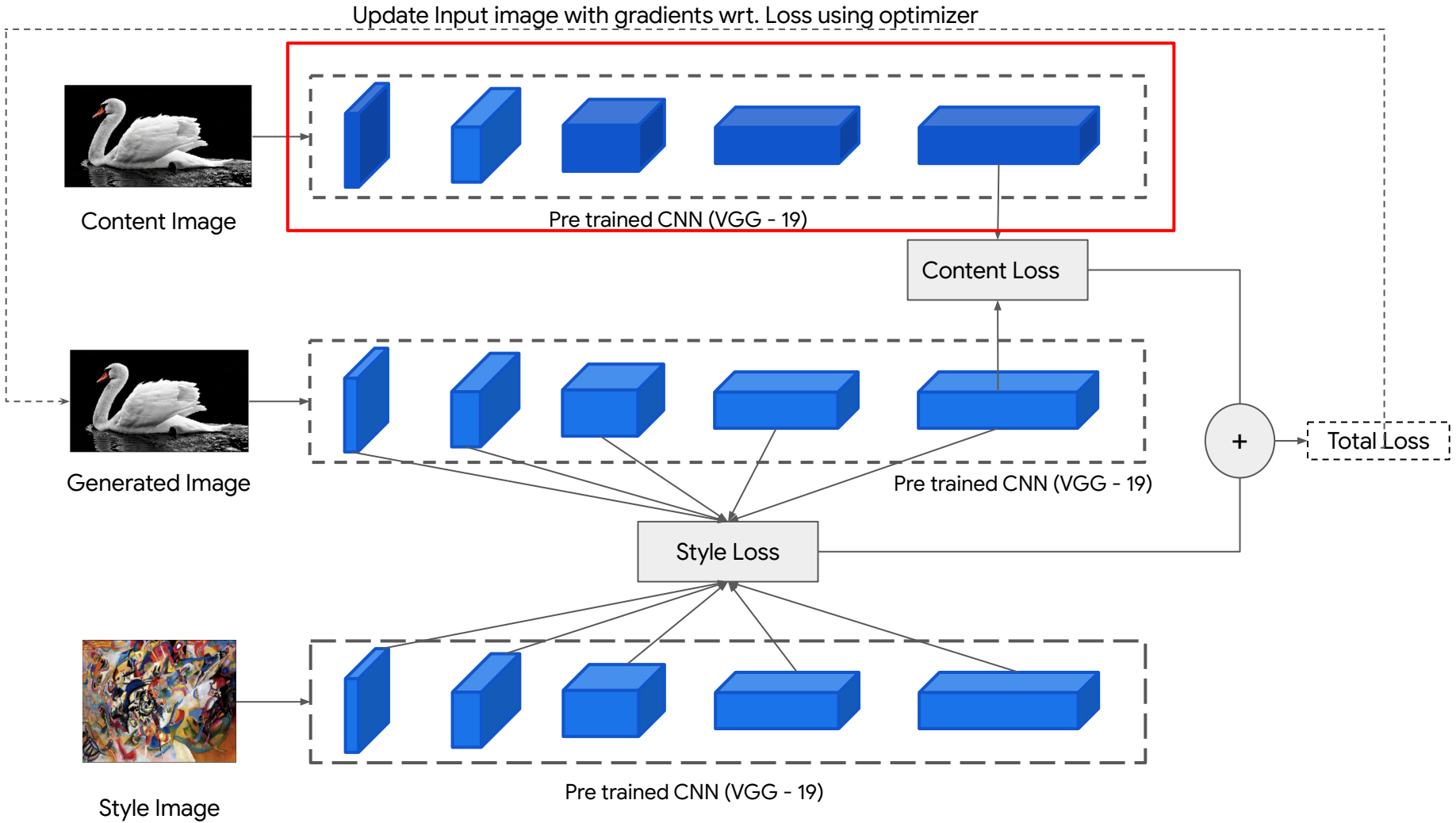
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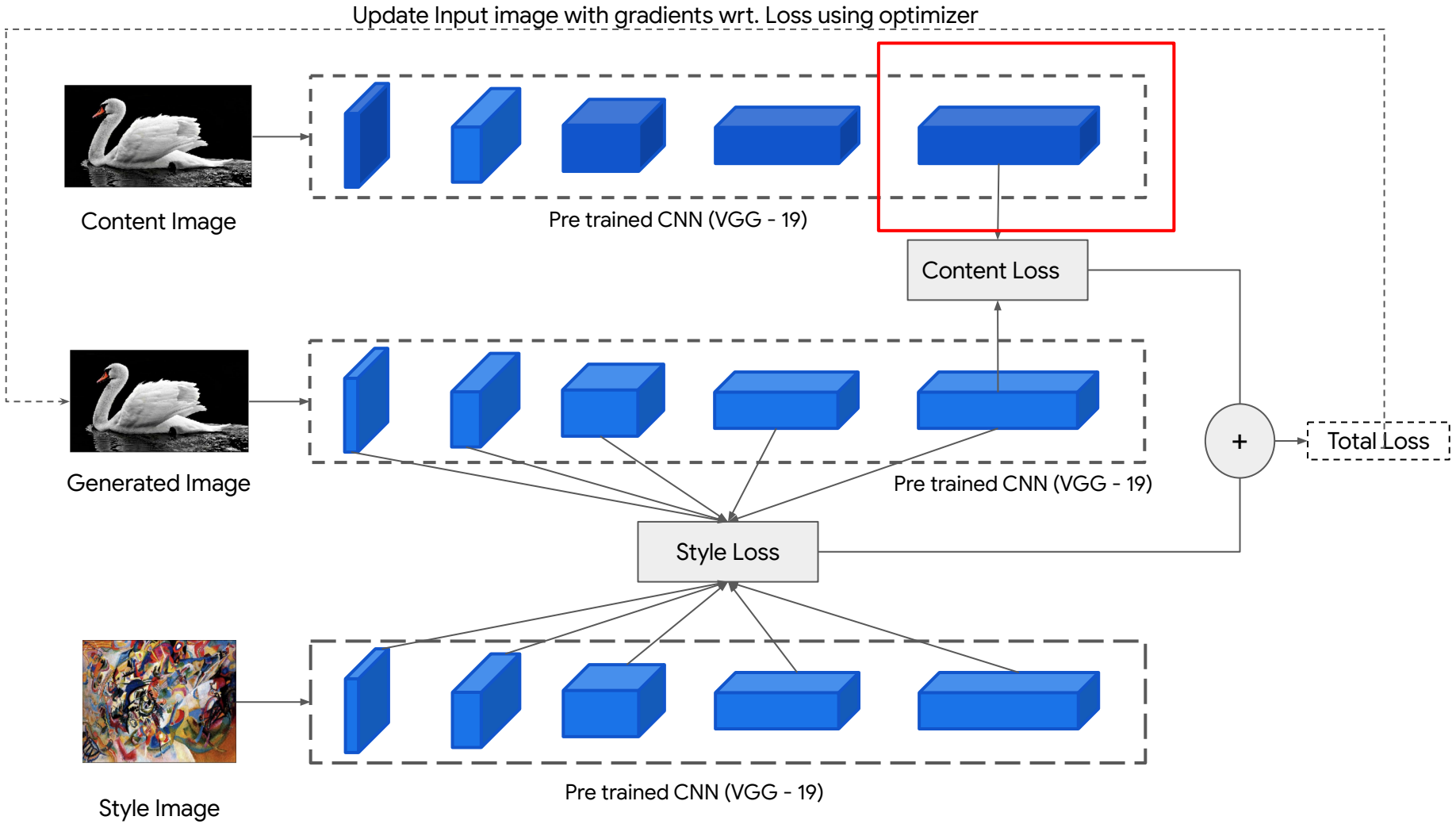
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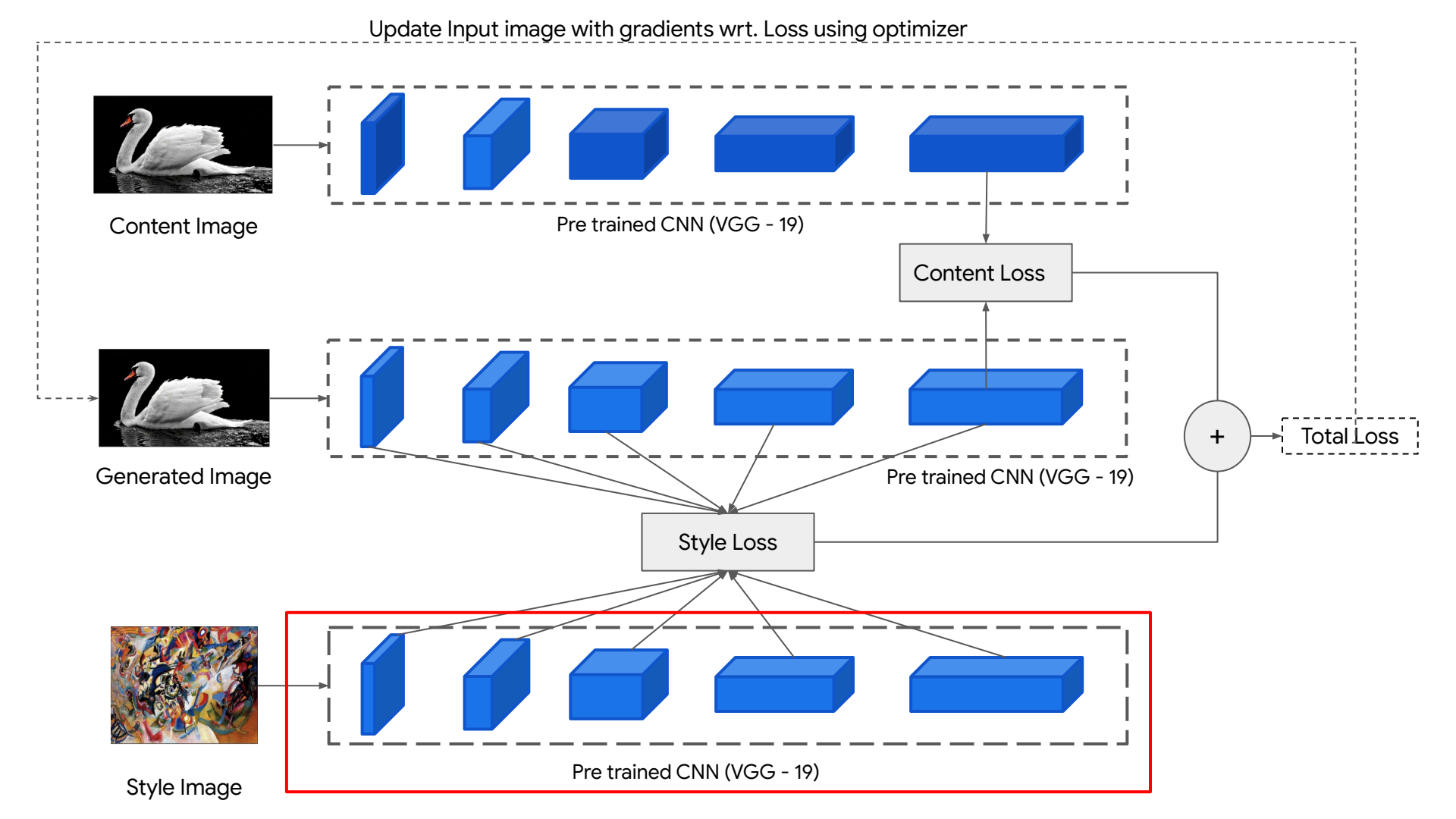
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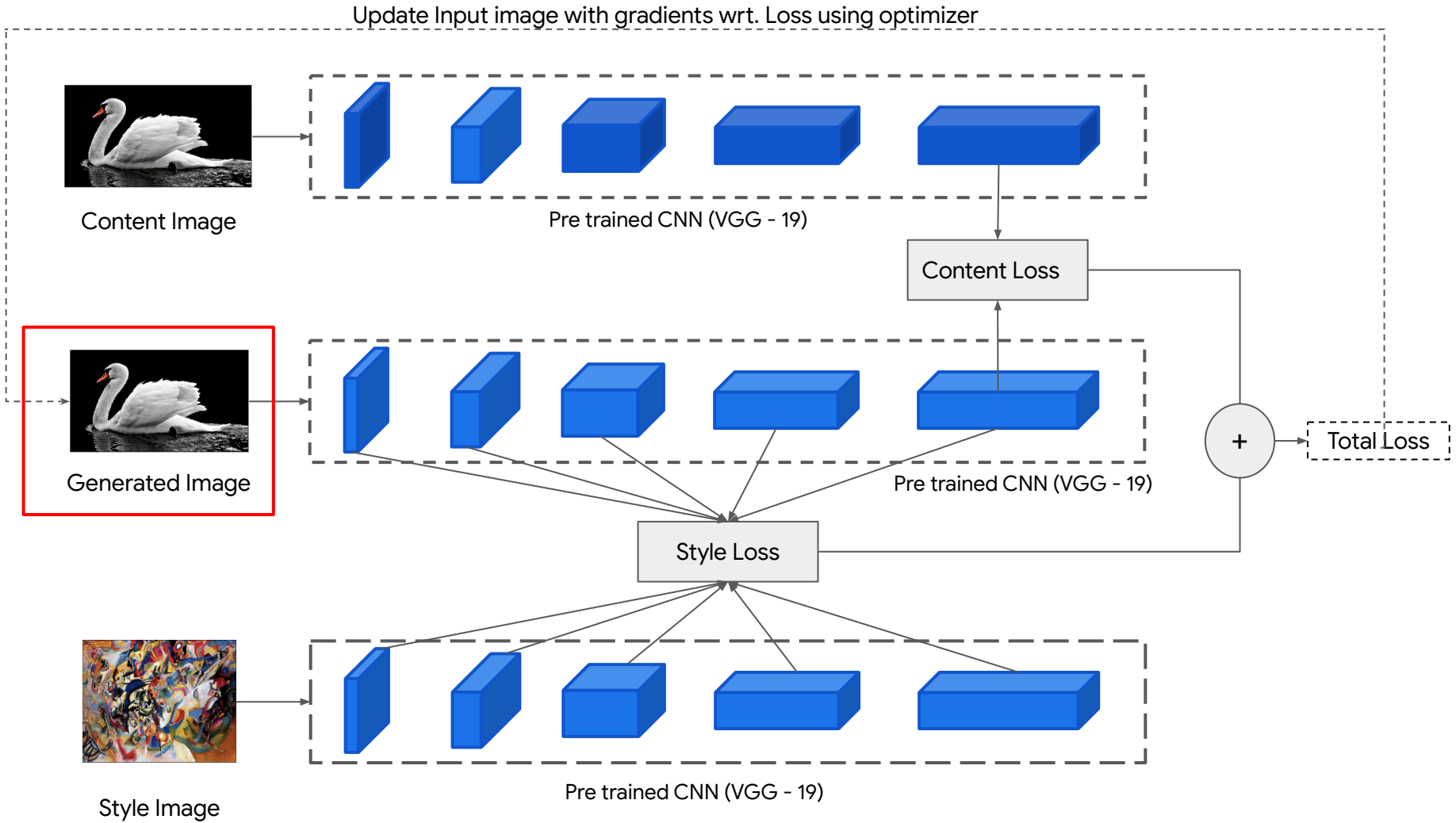
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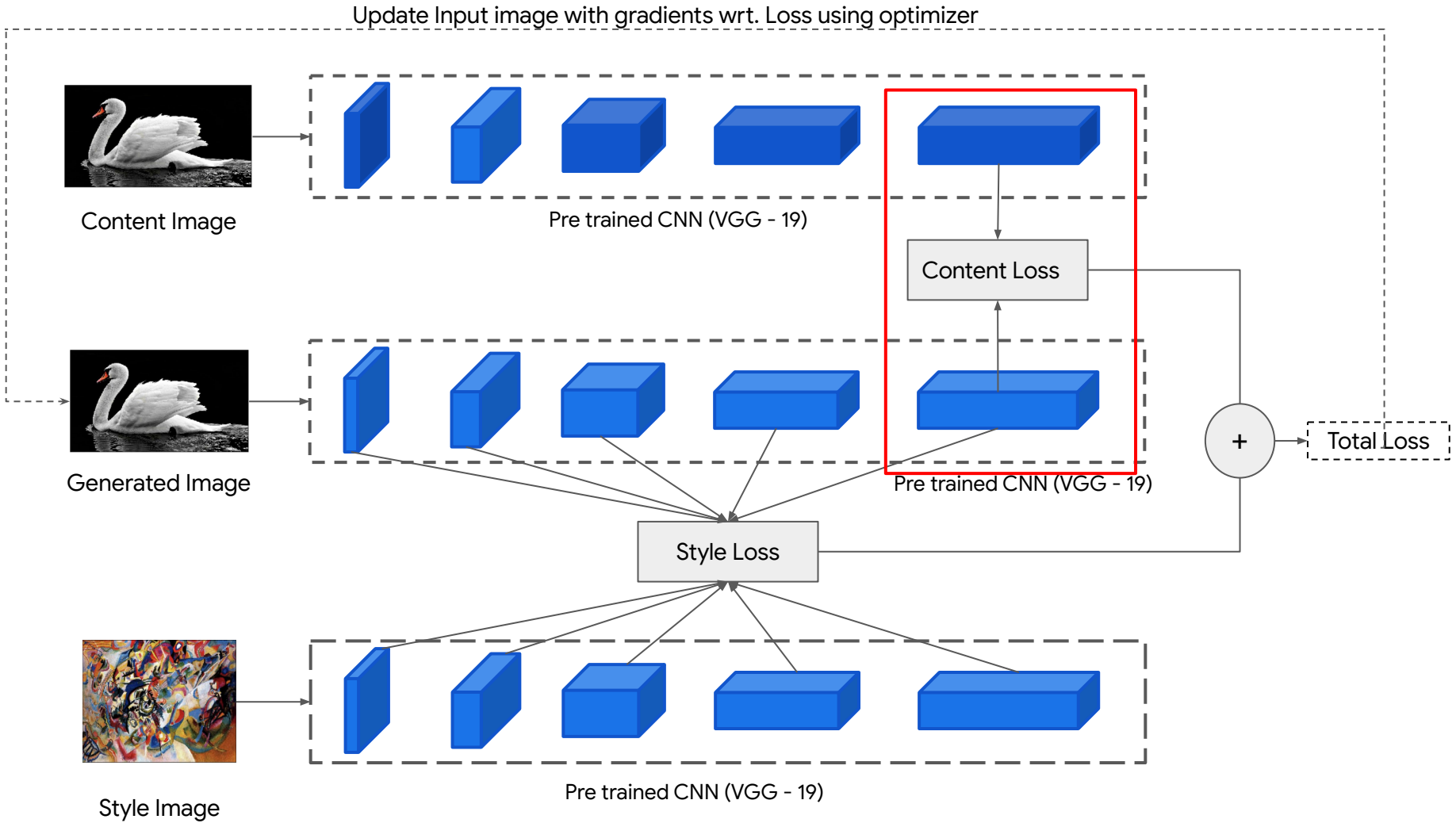
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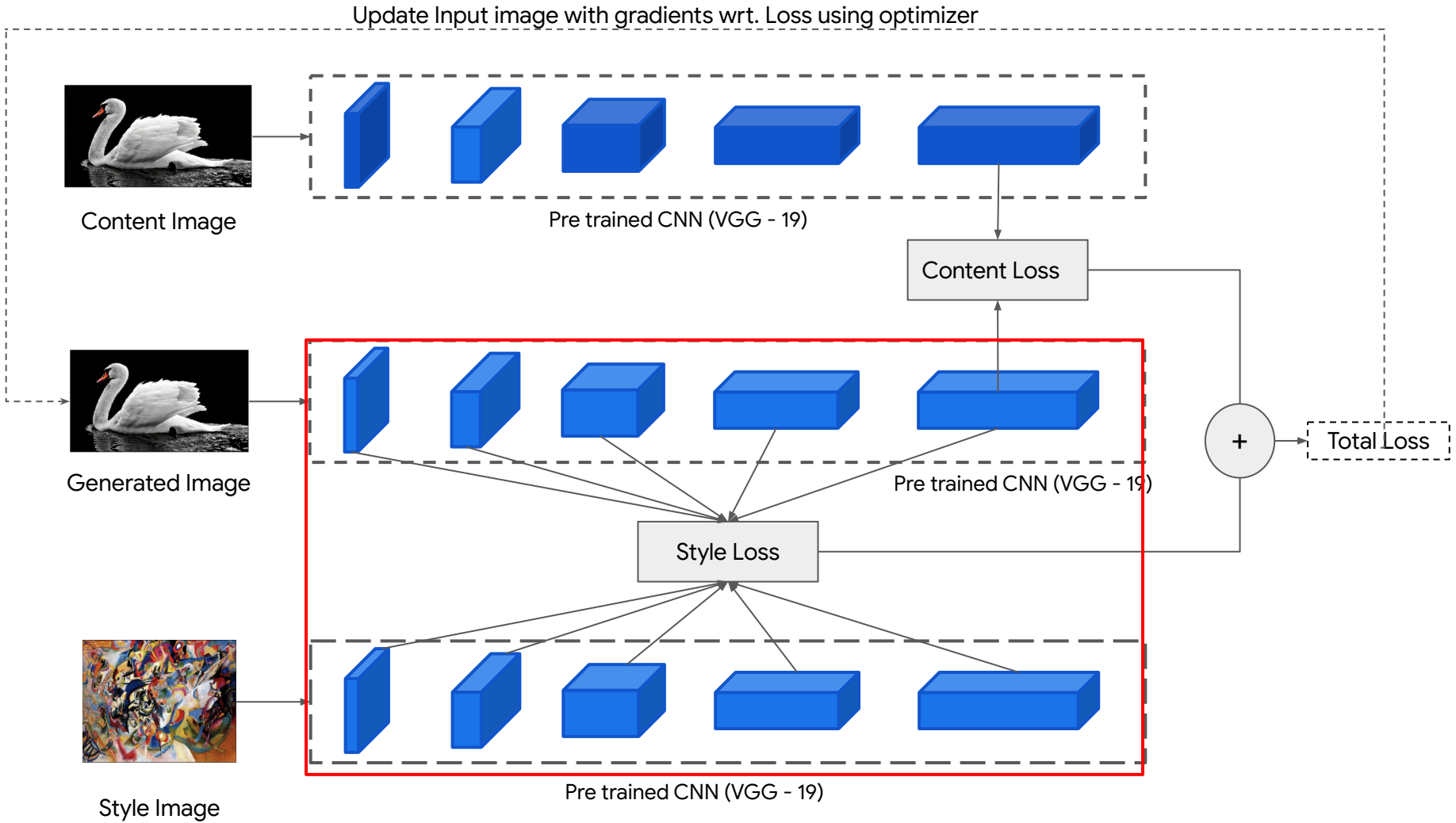
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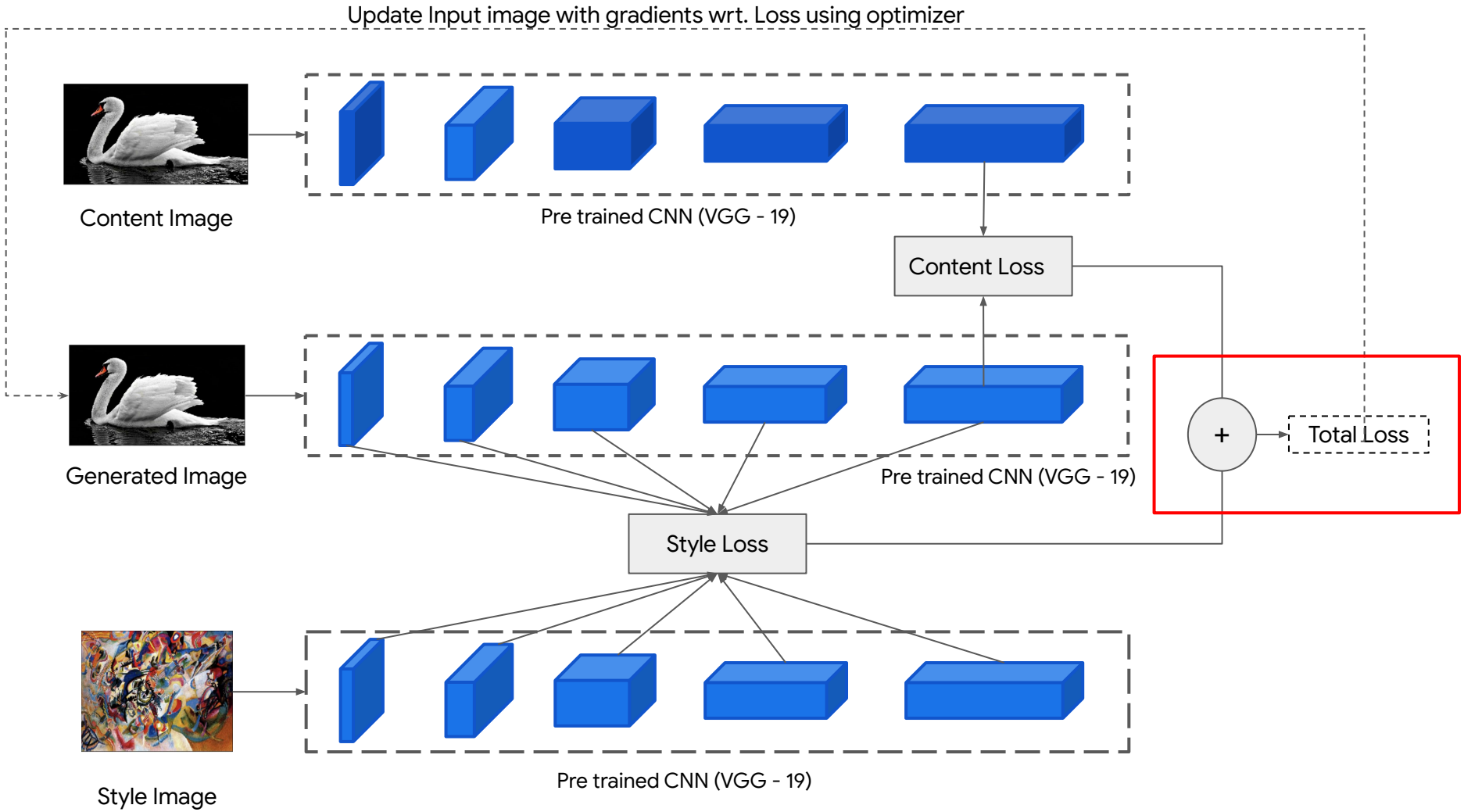
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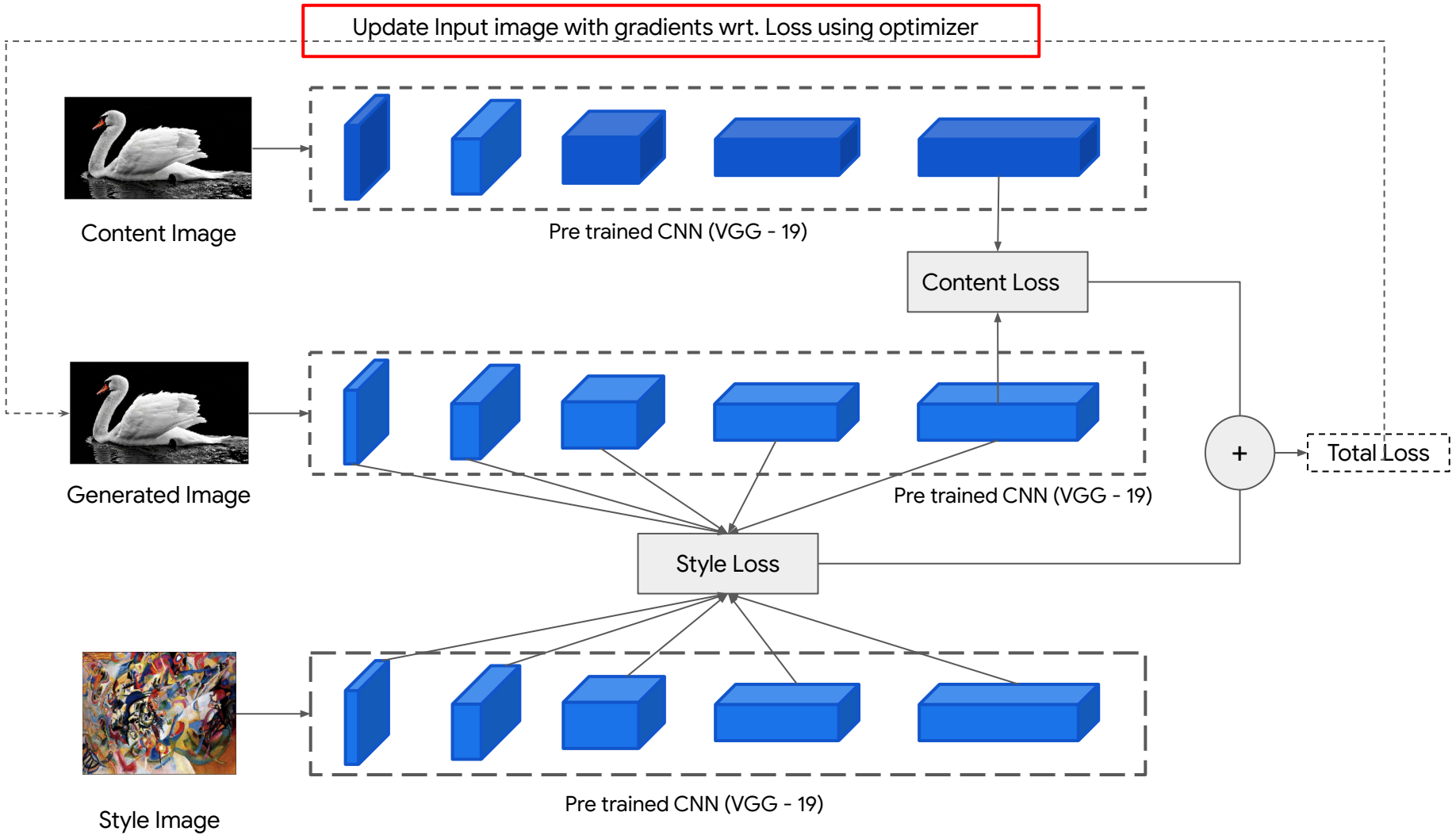
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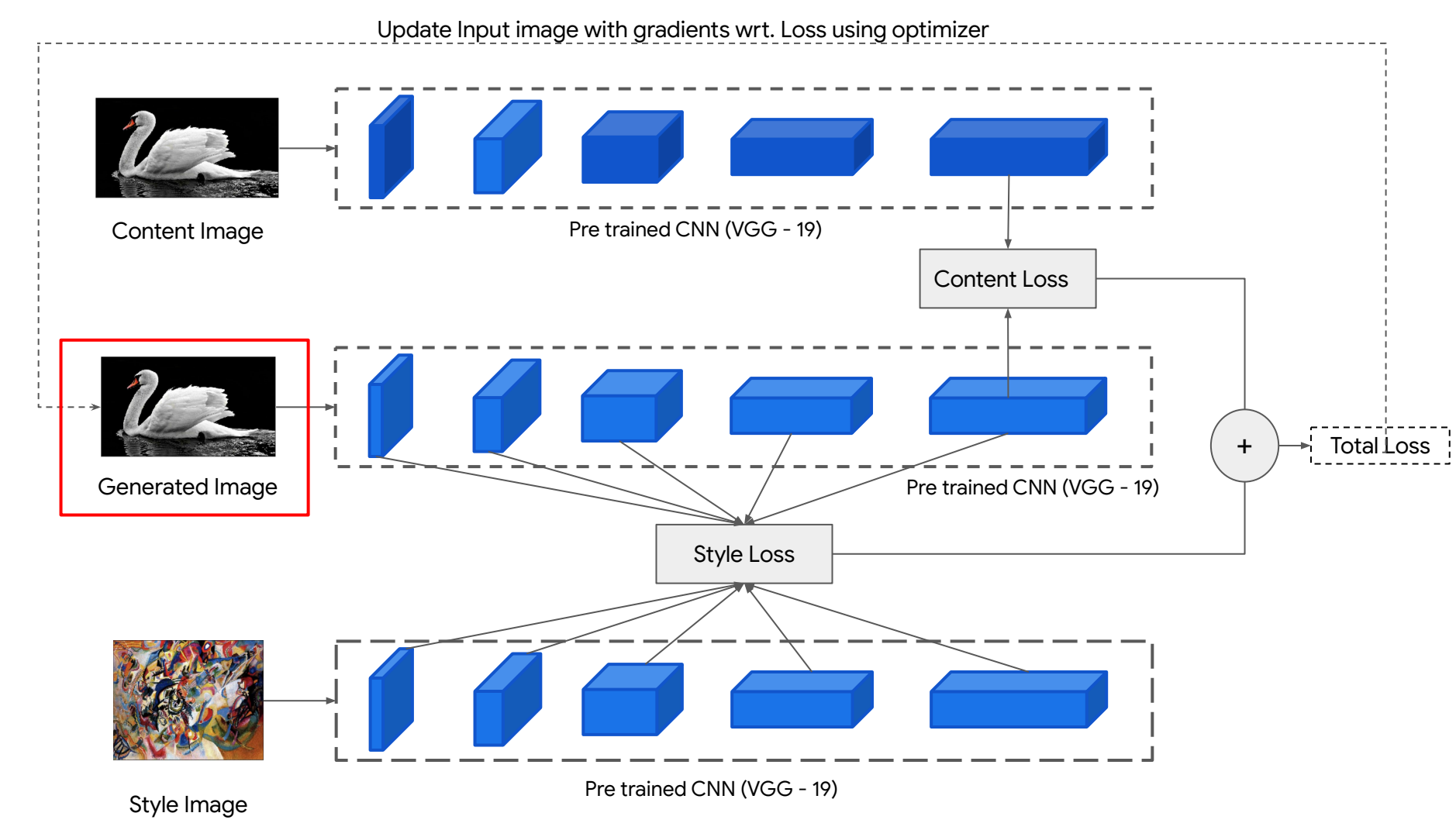
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2. Neural Style Transfer

Advantages

- Requires only single pair of content image and style image.

Drawbacks

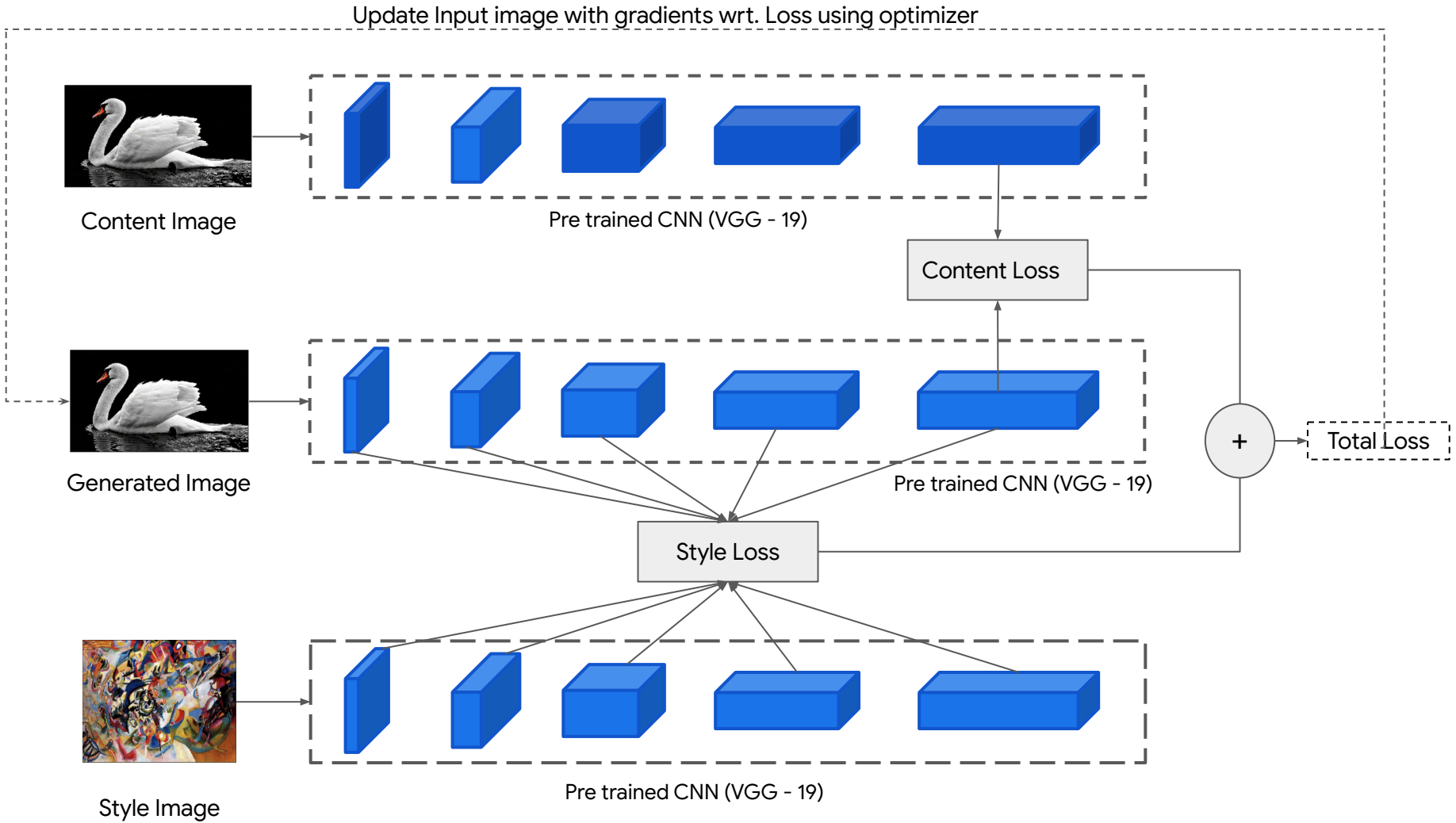
- Requires many passes for stylizing each image.
- Takes time in stylizing every time an input is given.

Perceptual Losses for Real-Time Style Transfer and Super Resolution

Justin Johnson / Alexandre Alahi / Fei Fei Li

https://cs.stanford.edu/people/jcjohns/eccv16/

Fig. 7. Example results for style transfer on 512 × 512 images by applying models trained on 256 × 256 images. The style images are the same as Figure 6.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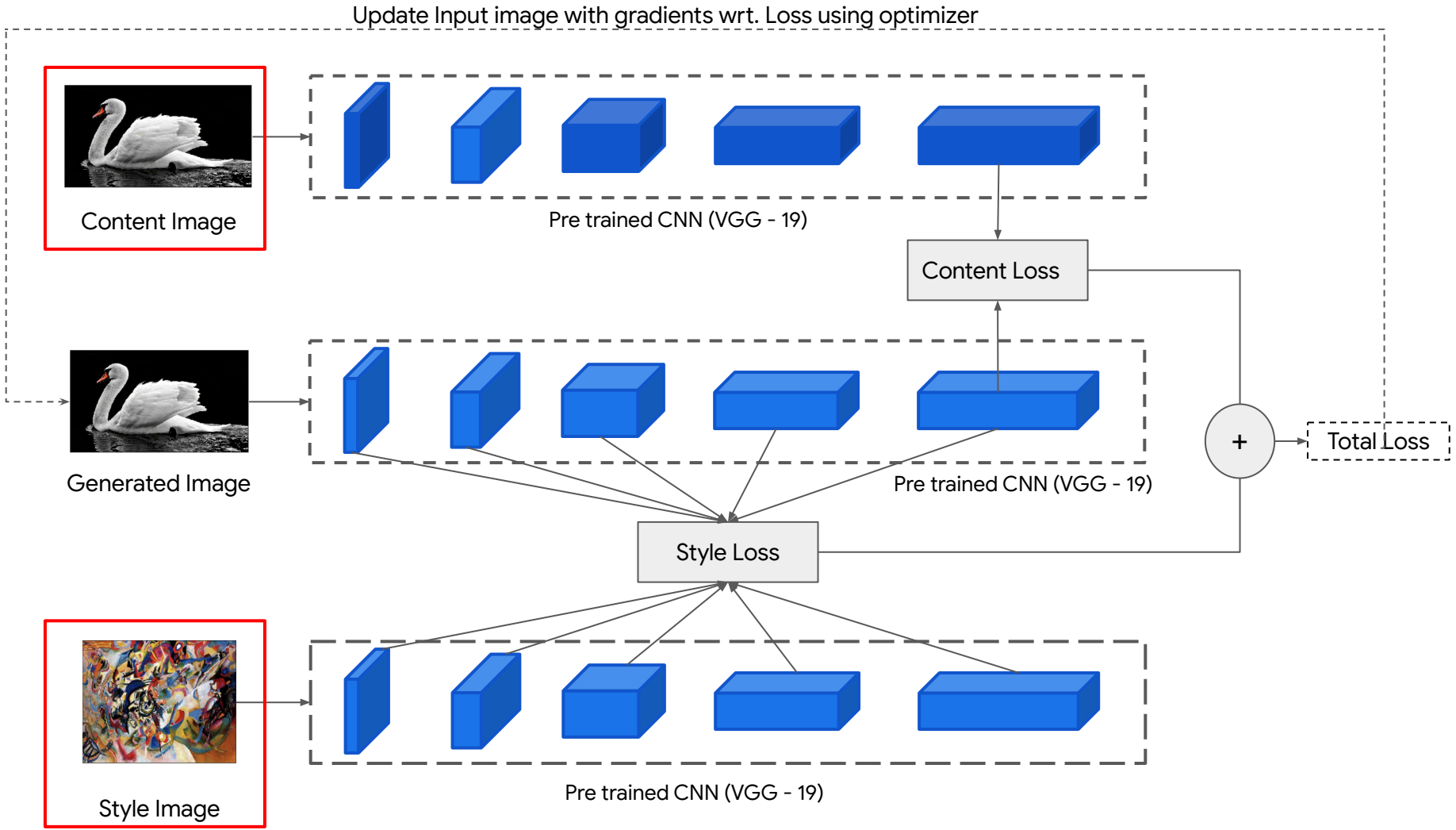
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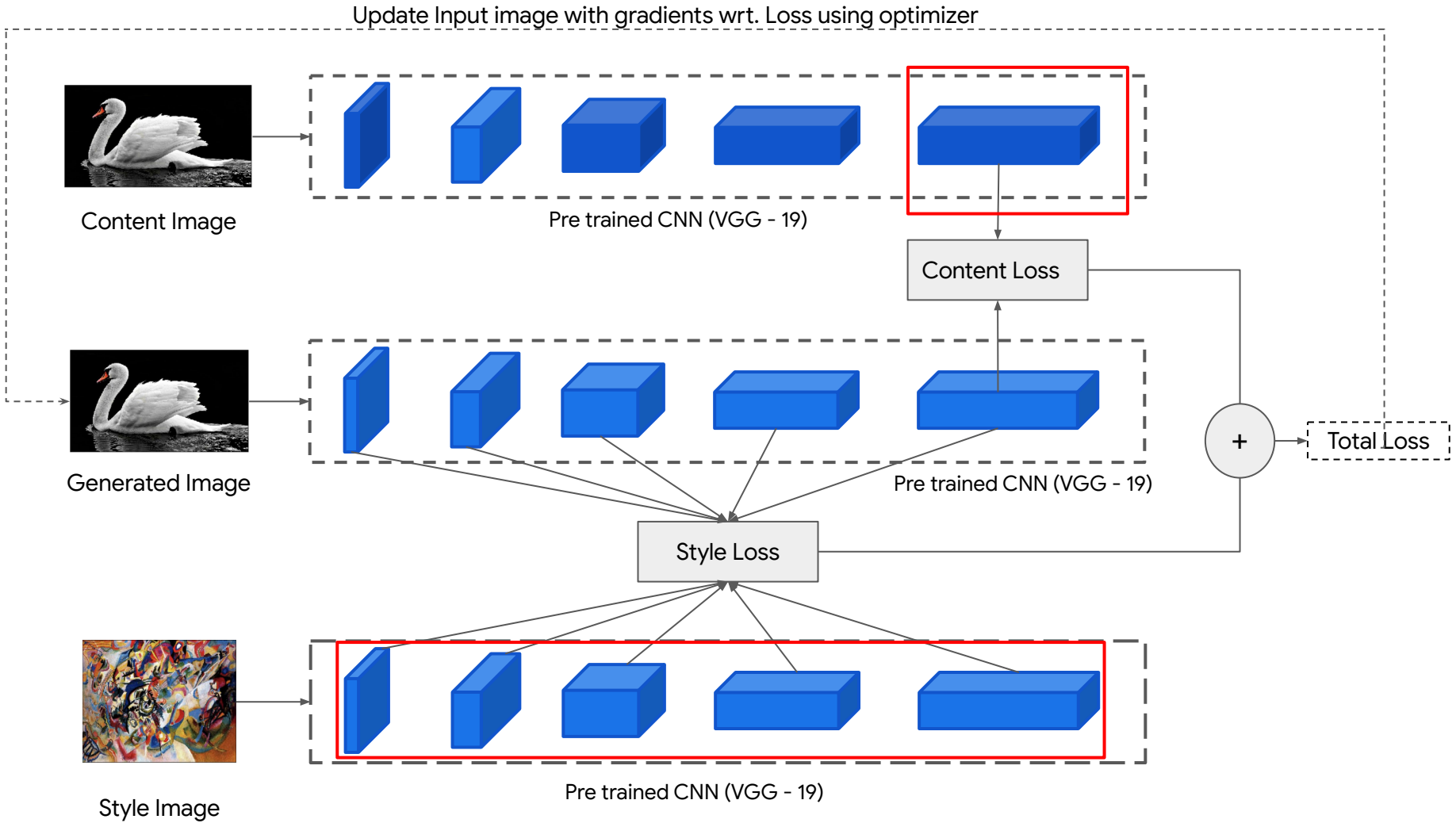
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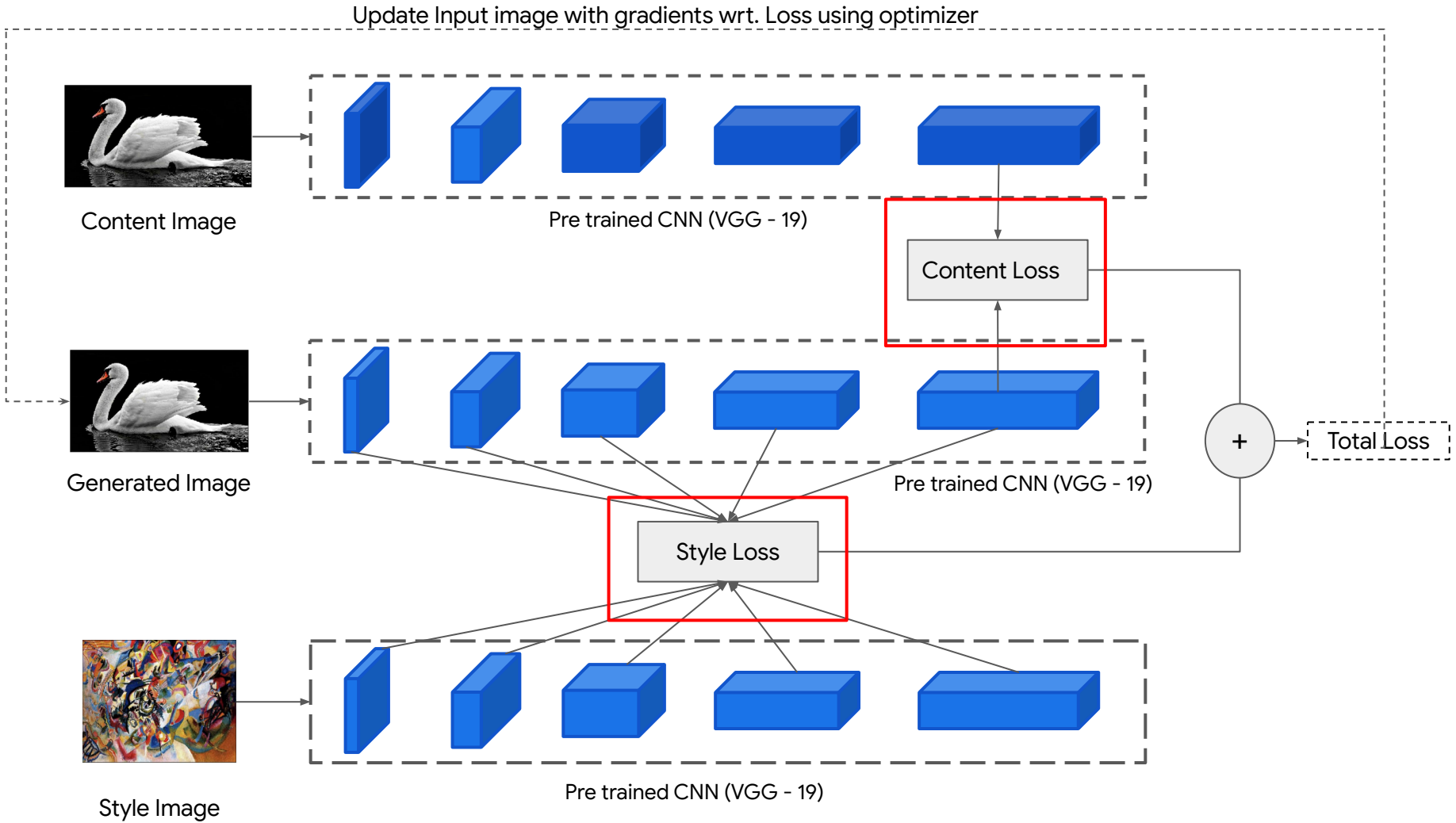
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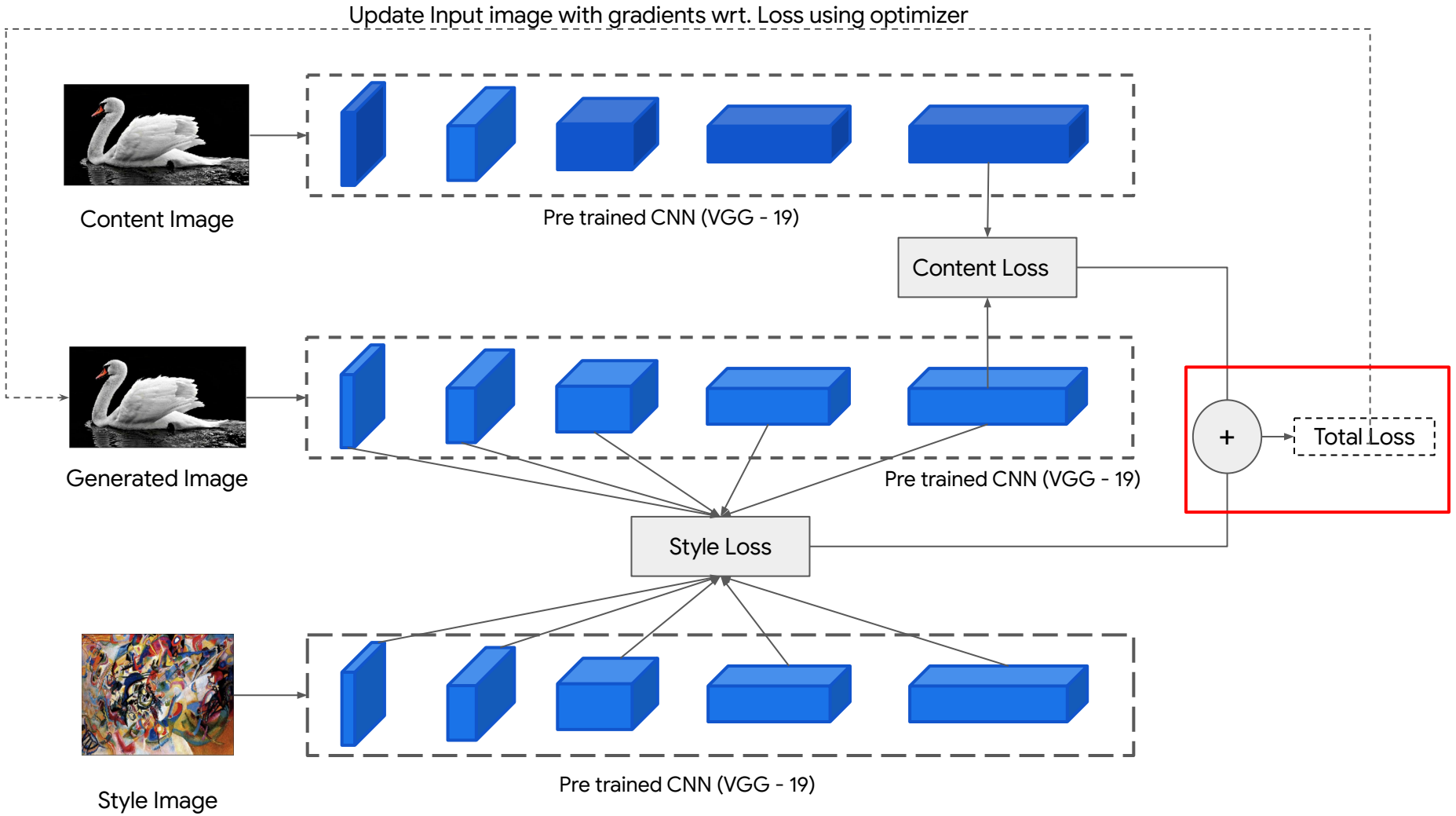
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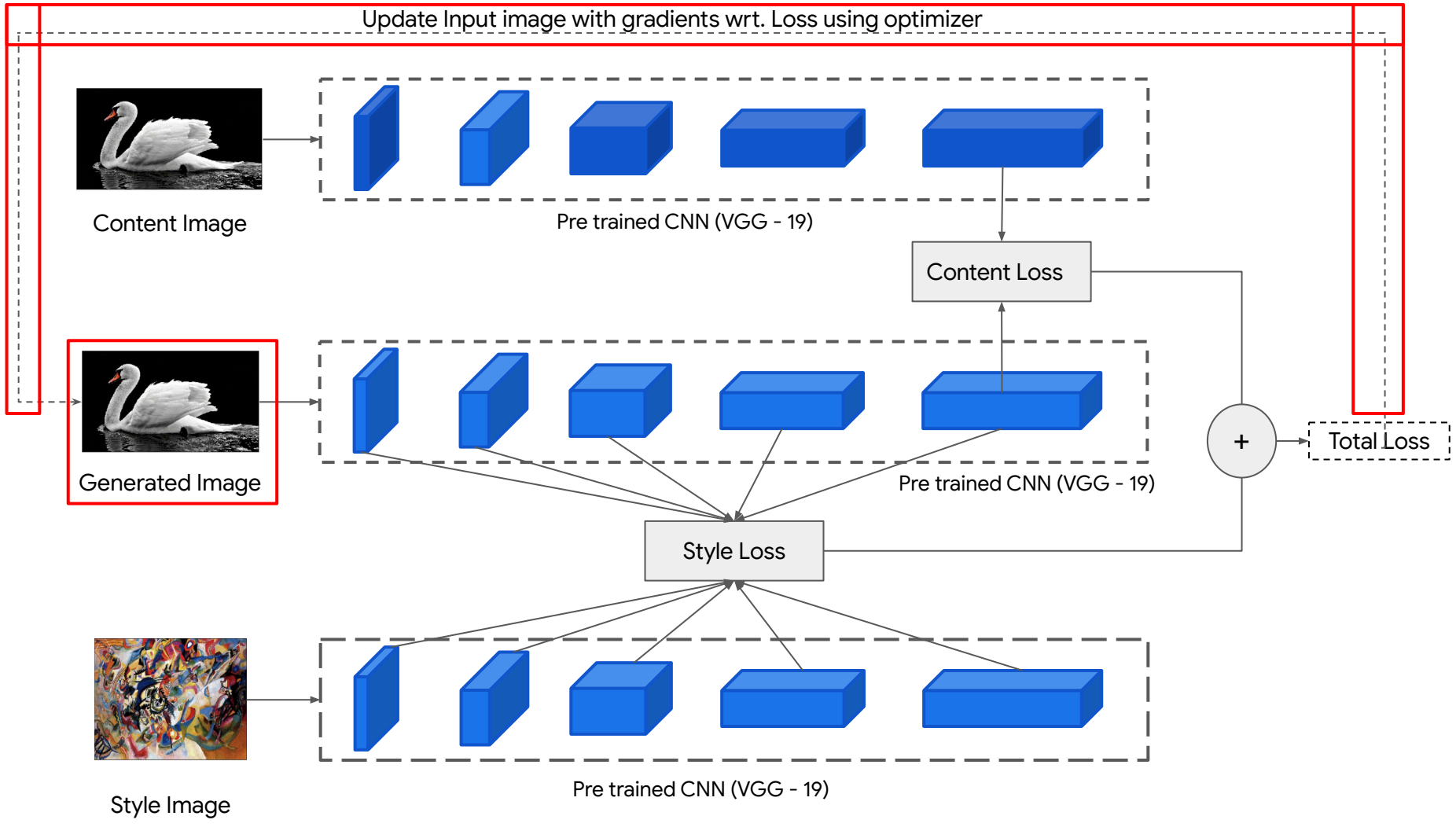
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Steps to Develop Neural Style Transfer

1. Preprocess, content & style images
2. Load pre trained model, define loss functions
3. Loop:
    a. Optimize and generate new image
    b. Visualize Outputs

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Load and Preprocess Images

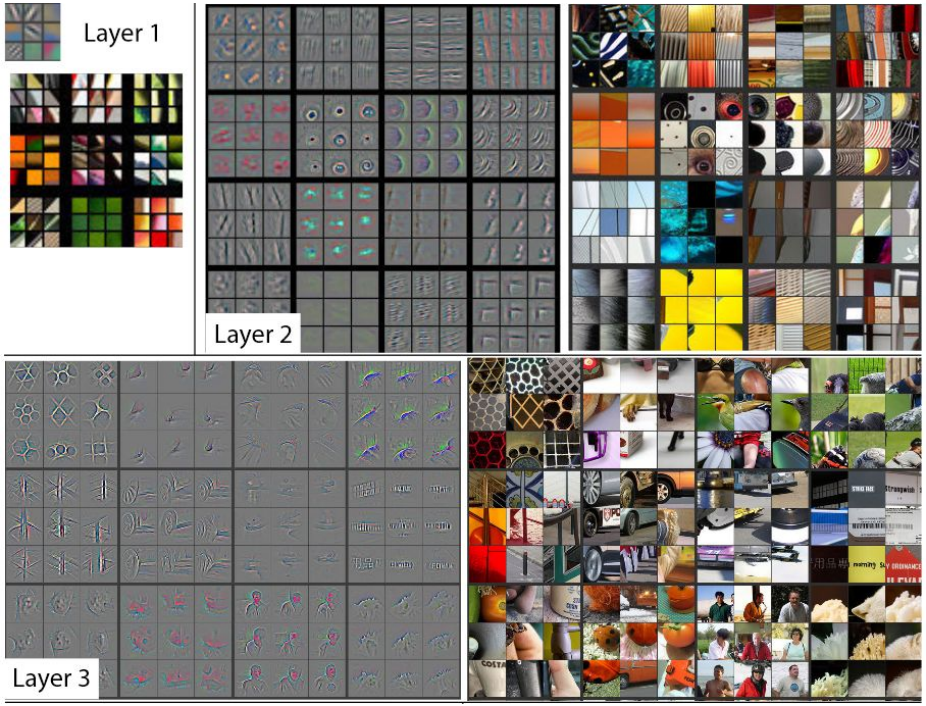
- VGG-19 pre trained on ‘imagenet’
- Accepts pixels values [0...255]
    - Don’t normalize to [0 ... 1]
- Expects centered pixel values

Keras Preprocess_input

```
def preprocess_image(image):
    ...
    image = tf.keras.applications.vgg19.preprocess_input(image)

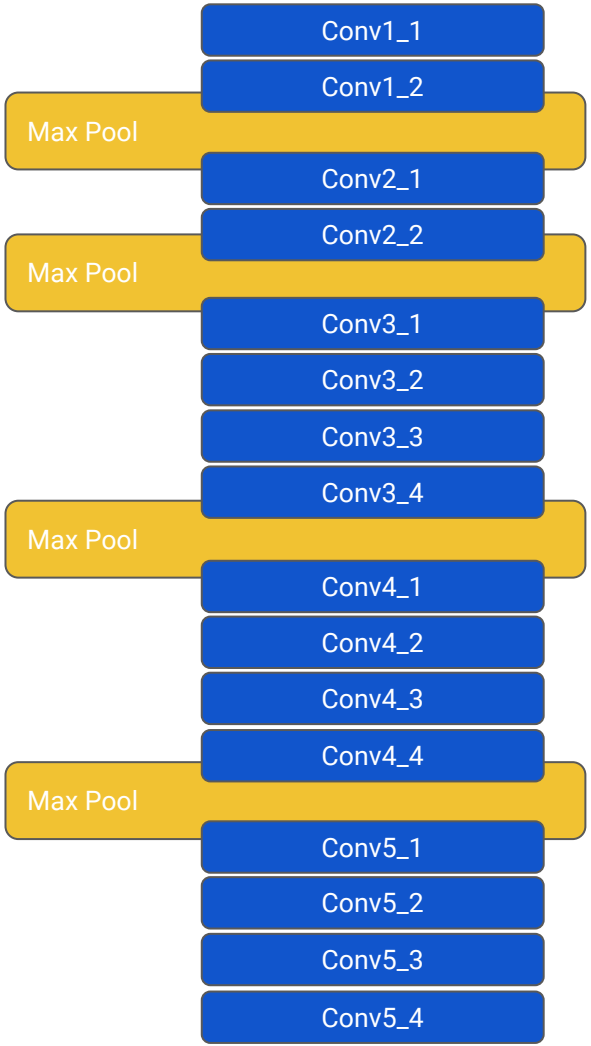
    return image
```

How CNN visualizes images?



https://arxiv.org/pdf/1311.2901.pdf

VGG-19 for style extraction



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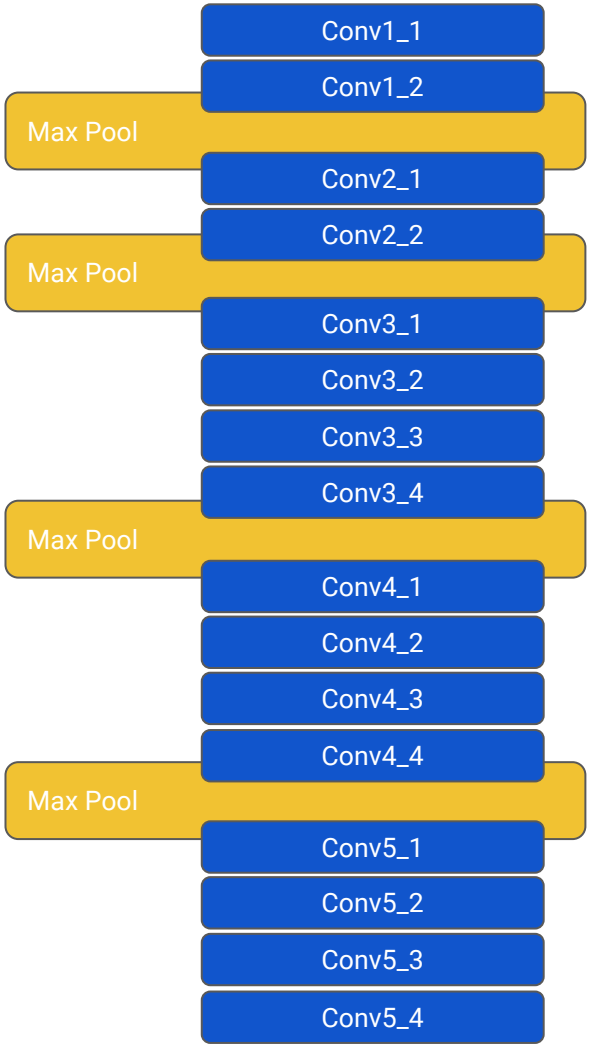
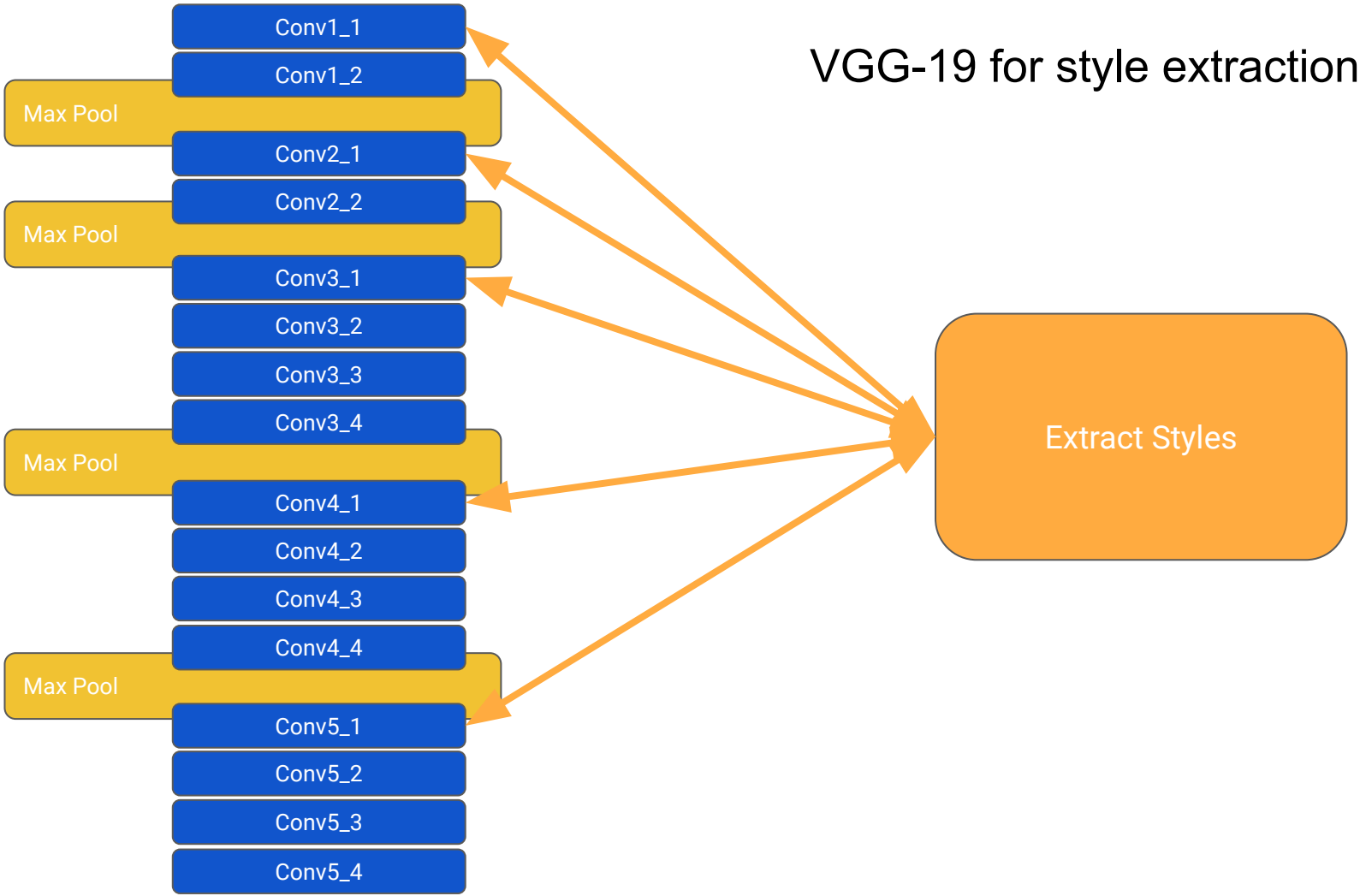


Extract Styles


VGG-19 for style extraction
Conv1_1
Conv1_2
Max Pool
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Max Pool
Conv3_1
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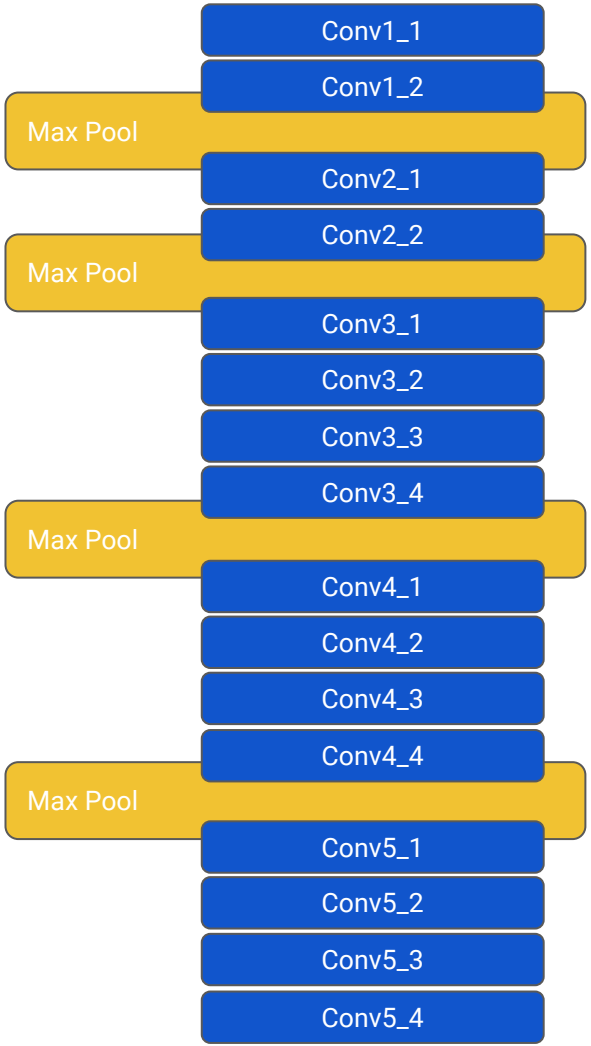
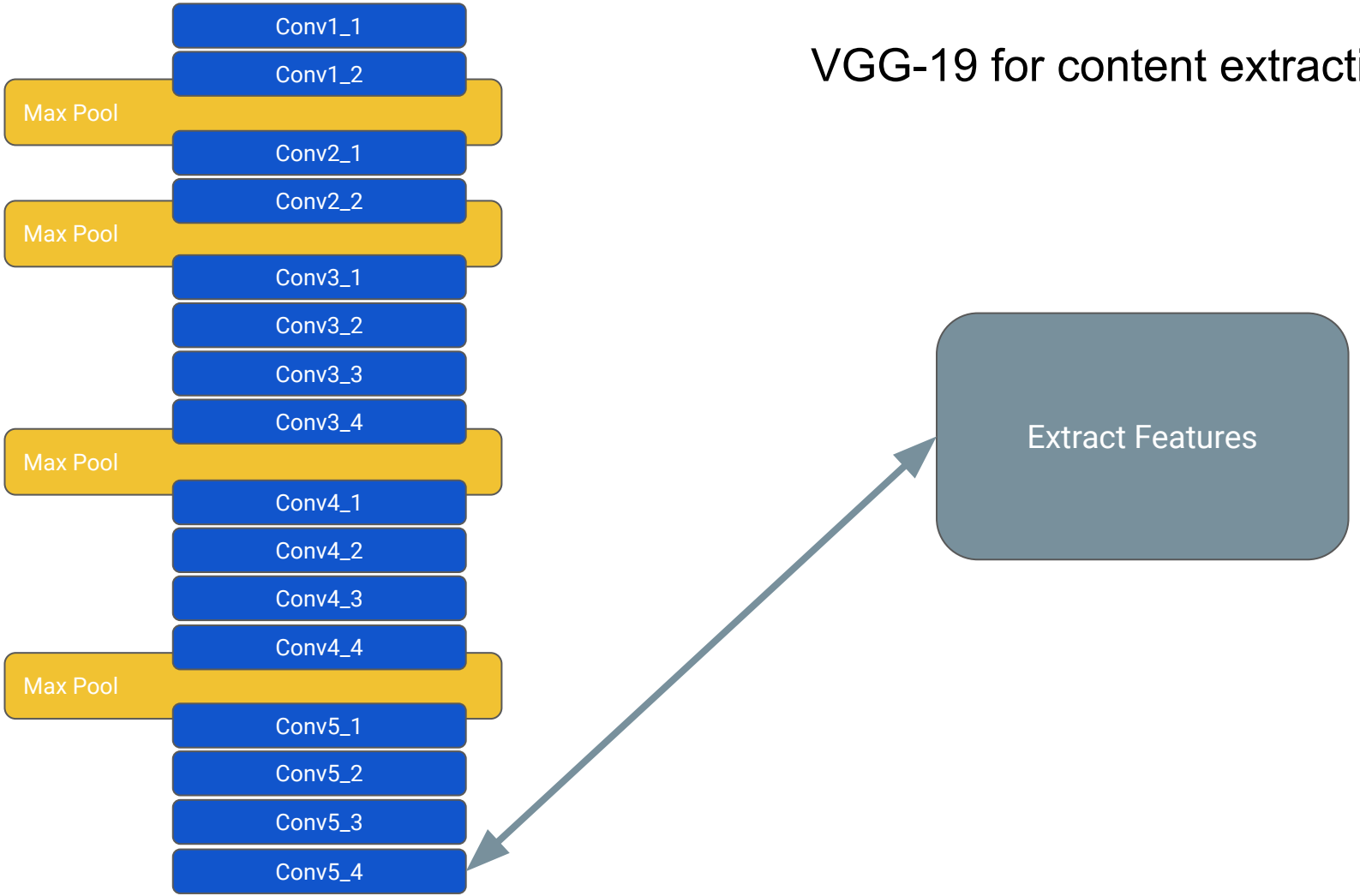
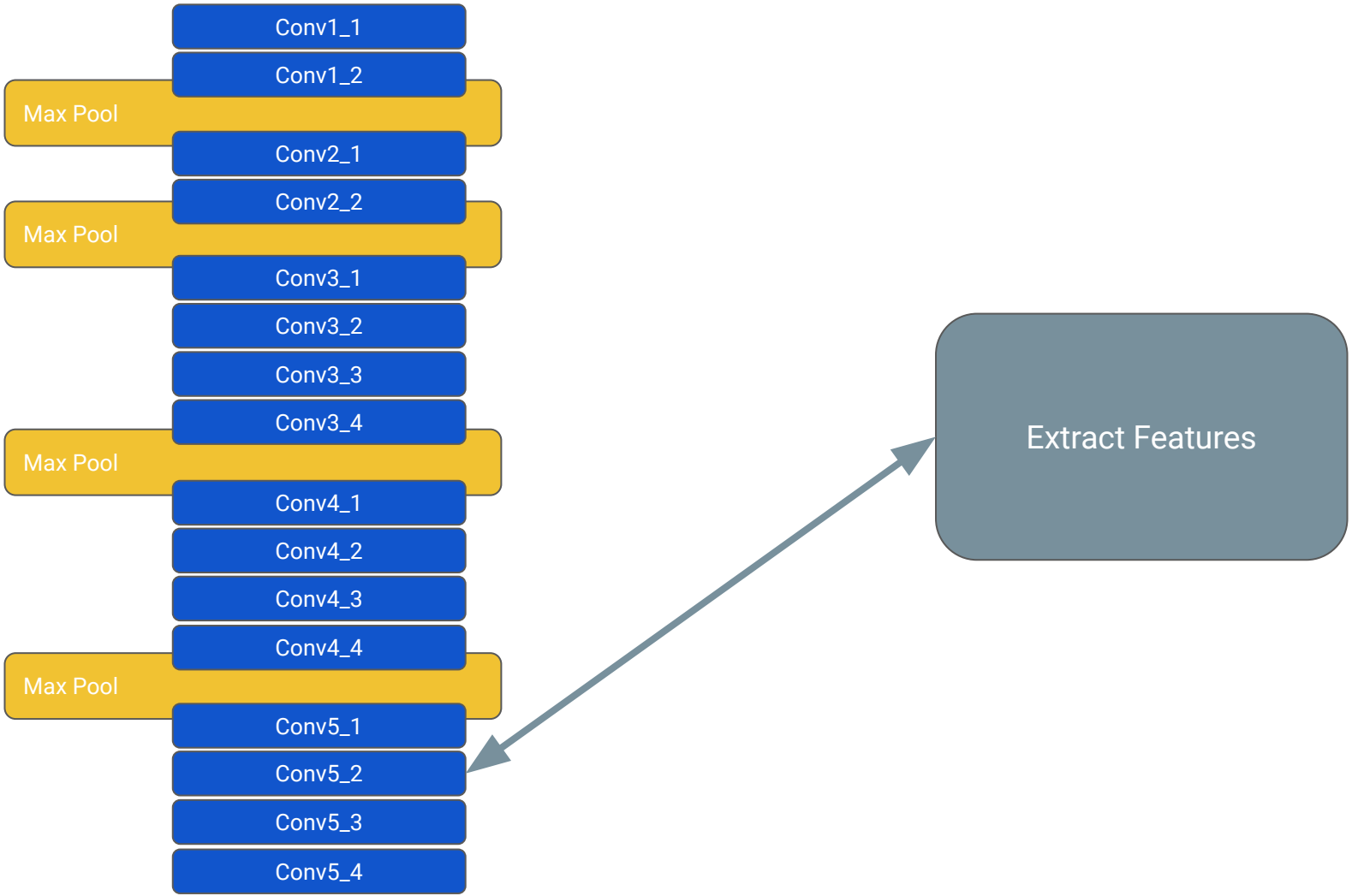
VGG-19 for content extraction



Extract Features

VGG-19 for content extraction

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Max Pool
Conv5_1
Conv5_2
Conv5_3
Conv5_4
Extract Features

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# Content layer where will pull our feature maps
content_layers = ['block5_conv2']

# Style layer of interest
style_layers = ['block1_conv1',
                'block2_conv1',
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                'block4_conv1',
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layer_names = content_layers + style_layers
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  """ Creates a vgg model that returns a list of intermediate output values."""
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  vgg.trainable = False

  outputs = [vgg.get_layer(name).output for name in layer_names]

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  vgg = tf.keras.applications.vgg19.VGG19(include_top=False, weights='imagenet')
  vgg.trainable = False

  outputs = [vgg.get_layer(name).output for name in layer_names]

  model = tf.keras.Model(inputs=vgg.input, outputs=outputs)

  return model
```

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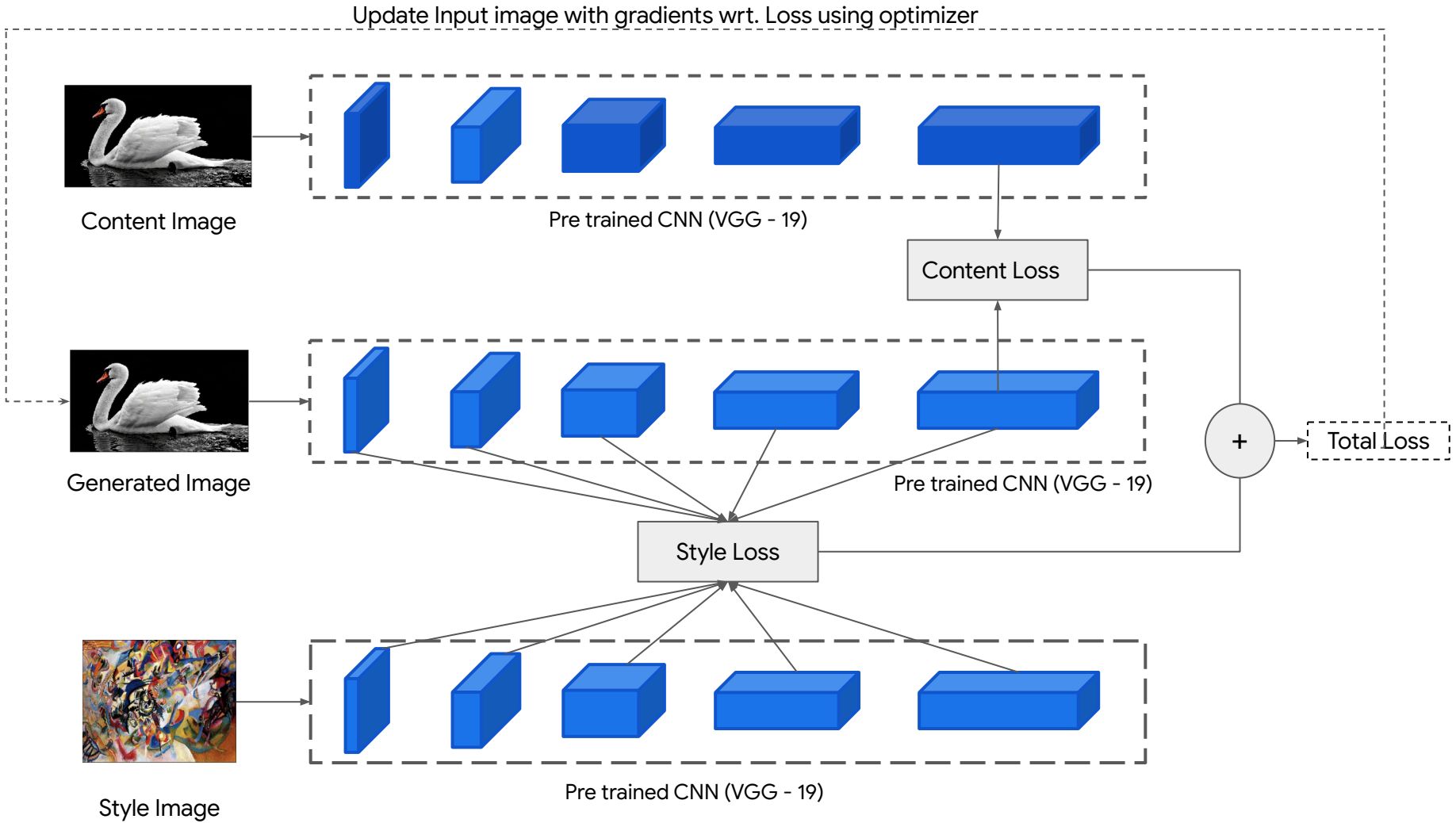
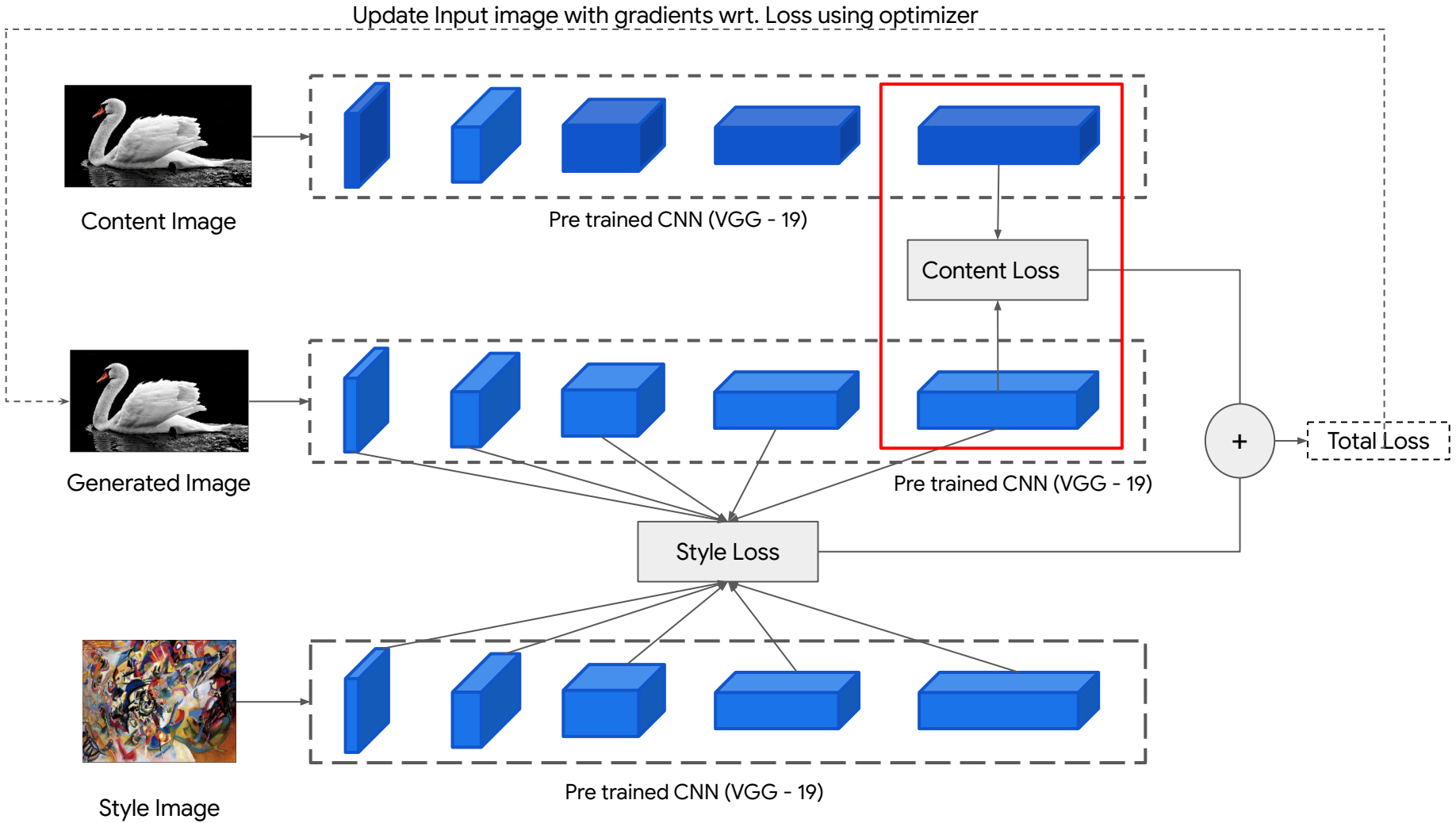
```


Update Input image with gradients wrt. Loss using optimizer
Content Image
Pre trained CNN (VGG - 19)
Content Loss
Generated Image
Pre trained CNN (VGG - 19)
+
Total Loss
Style Loss
Style Image
Pre trained CNN (VGG - 19)


Update Input image with gradients wrt. Loss using optimizer
Content Image
Pre trained CNN (VGG - 19)
Content Loss
Generated Image
Pre trained CNN (VGG - 19)
+
Total Loss
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Style Image
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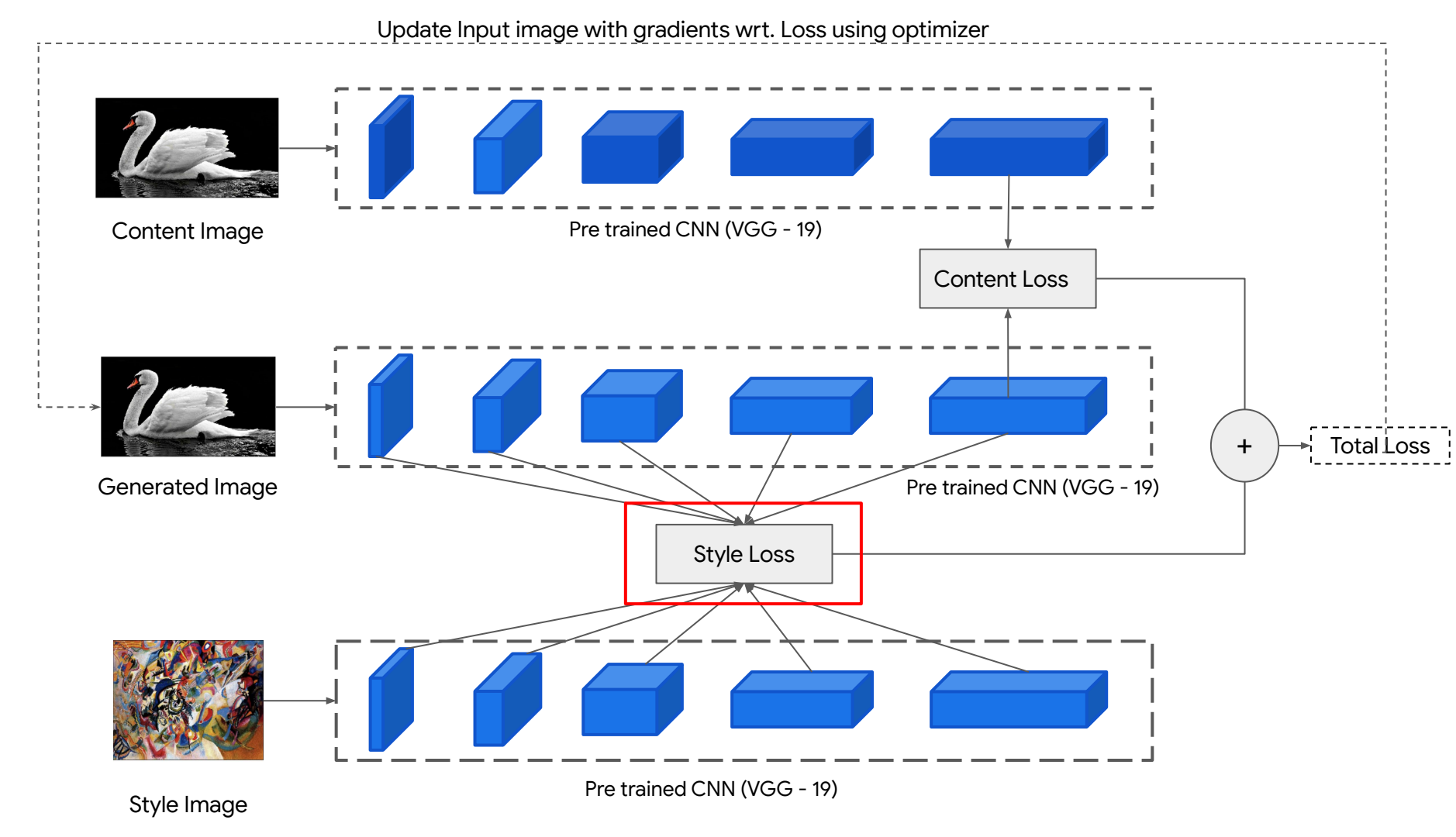
Update Input image with gradients wrt. Loss using optimizer
Content Image
Pre trained CNN (VGG - 19)
Content Loss
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+
Total Loss
Style Loss
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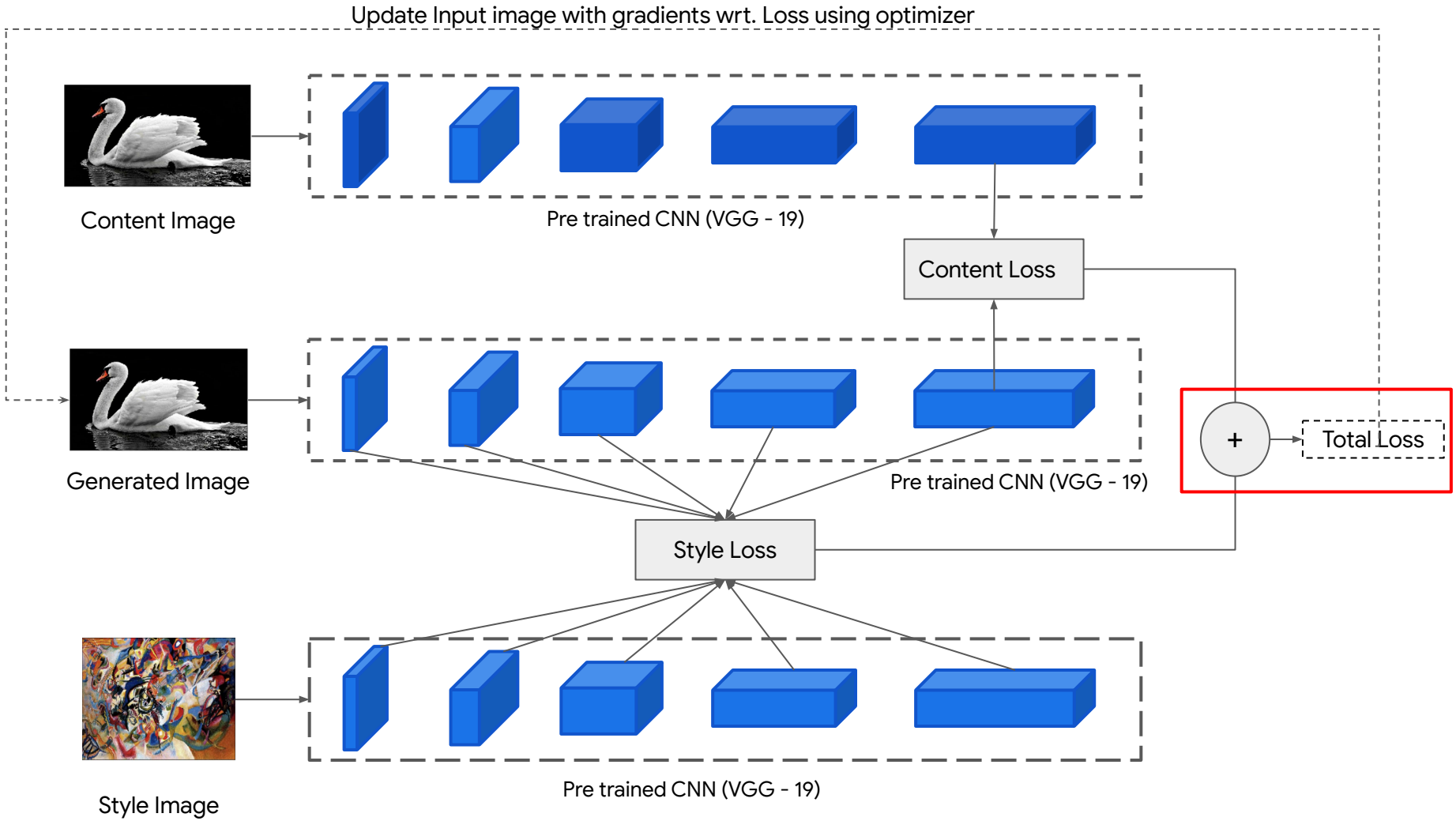

Update Input image with gradients wrt. Loss using optimizer
Content Image
Pre trained CNN (VGG - 19)
Content Loss
Generated Image
Pre trained CNN (VGG - 19)
+
Total Loss
Style Loss
Style Image
Pre trained CNN (VGG - 19)

Total Loss

$$L_{total} = L_{content} + L_{style}$$

Total Loss

$$L_{total} = \alpha L_{content} + \beta L_{style}$$

α : Content Weight

β : Style Weight

Total Loss

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

α : Content Weight

β : Style Weight

Total Loss

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

$\vec{p}$: Content Image (Original Photograph)

$\vec{x}$: Generated Image initialized to Input Image

α : Content Weight

β : Style Weight

Total Loss

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

$\vec{a}$: Style Image

$\vec{x}$: Generated Image initialized to Input Image

α : Content Weight

β : Style Weight

Total Loss

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

$\vec{p}$: Content Image (Original Photograph)

$\vec{a}$: Style Image

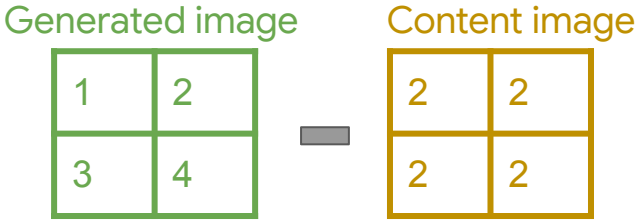
$\vec{x}$: Generated Image initialized to Input Image

α : Content Weight

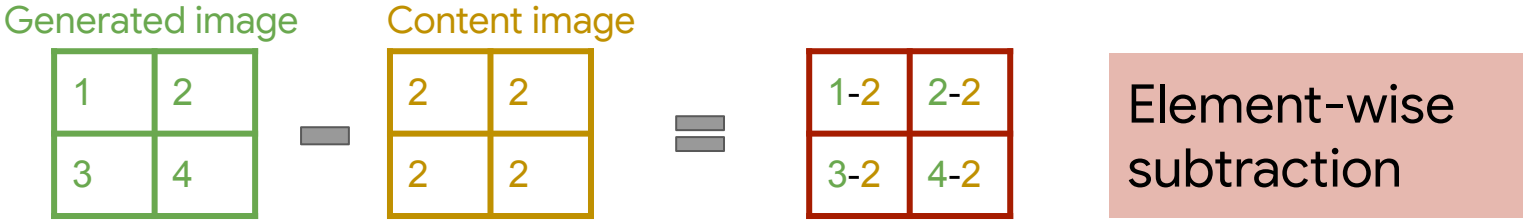
β : Style Weight

Content Loss

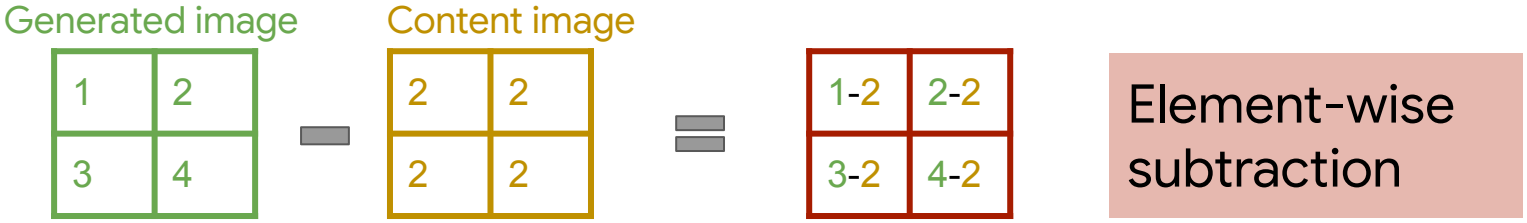
Content Loss



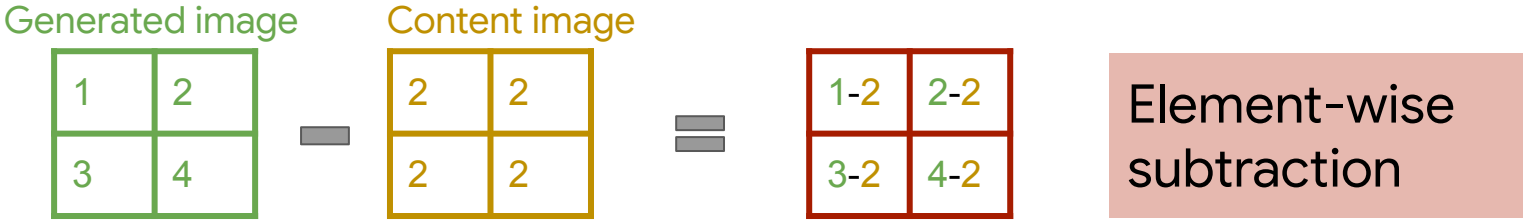
Content Loss



Content Loss



Content Loss



Content Loss

Generated image

1	2
3	4

−

Content image

2	2
2	2

=

1-2	2-2
3-2	4-2

Element-wise subtraction

$(1-2)^2$	$(2-2)^2$
$(3-2)^2$	$(4-2)^2$

Element-wise square

$1^2 + 0^2 + 1^2 + 2^2 =$ 6

Reduce sum

$(½)\ 6 =$ 3

weight

Content Loss

$$L_{content}(\overrightarrow{p}, \overrightarrow{x}, l) = \frac{1}{2}\sum_{i,j}(F^l_{i,j} - P^l_{i,j})^2$$

l: layer *l*

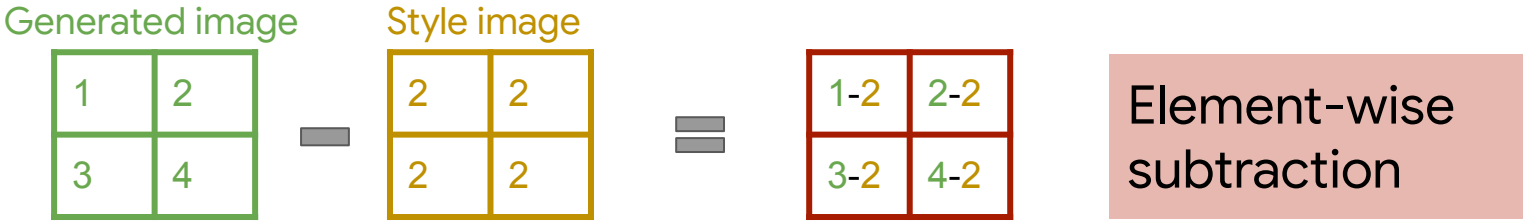
$\mathbf{F}^{l}_{ij}$: Content representation of generated image x in layer l (Activation of *i*th feature map at position *j* in layer *l of generated image)*.

$\mathbf{P}^{l}_{ij}$: Content representation of content image p in layer l. (Activation of the *i* th feature map at position *j* in layer *l* of content image.)

Content Loss - In Practice

```
def get_content_loss(features, targets):
   return 0.5 * tf.reduce_sum(tf.square(features - targets))
```

Style Loss


Generated image
1
2
3
4
−
Style image
2
2
2
2
=
1-2
2-2
3-2
4-2
Element-wise subtraction
$(1-2)^2$
$(2-2)^2$
$(3-2)^2$
$(4-2)^2$
Element-wise square
$1^2 + 0^2 + 1^2 + 2^2 =$
6
Reduce sum
$(?/_?)\ 6 =$
?
weight

Style Loss

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{i,j}^l - A_{ij}^l)^2$$

l: layer *l*

$\mathbf{A}^l_{ij}$: Style Representation(Gram Matrix) of style image a.

$\mathbf{G}^l_{ij}$: Style Representation(Gram Matrix) of generated image x

Style Loss

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{i,j}^l - A_{ij}^l)^2$$

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l: layer *l*

$\mathbf{A}^l_{ij}$: Style Representation(Gram Matrix) of style image a.

$\mathbf{G}^l_{ij}$: Style Representation(Gram Matrix) of generated image x

Gram Matrix

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l}$$

G_{ij}^{l}: inner product between vectorized feature maps i and j in layer l.

Gram Matrix - In Practice

```
def gram_matrix(input_tensor):
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensorT, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

https://numpy.org/doc/stable/reference/generated/numpy.einsum.html

Get Style Feature Representation at Layers

```
def get_style_image_features(image):
  preprocessed_style_image = preprocess_image(image)
  style_outputs = vgg(preprocessed_style_image)
  gram_style_features =
     [gram_matrix(style_layer) for style_layer in style_outputs[:num_style_layers]]

  return gram_style_features
```

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  return gram_style_features
```

Get Style Feature Representation at Layers

```
def get_style_loss(features, targets):
  return tf.reduce_mean(tf.square(features - targets))
```

Total Loss

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x})$$

```
def get_style_content_loss(style_targets, style_outputs,
                           content_targets, content_outputs,
                           style_weight, content_weight):

  style_loss = tf.add_n([get_style_loss(style_output, style_target)
                           for style_output, style_target in zip(style_outputs, style_targets)])

  style_loss *= style_weight / num_style_layers

  content_loss = tf.add_n([get_content_loss(content_output, content_target)
                  for content_output, content_target in zip(content_outputs, content_targets)])
  content_loss *= content_weight / num_content_layers

  loss = style_loss + content_loss
  return loss
```

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  style_loss *= style_weight / num_style_layers

  content_loss = tf.add_n([get_content_loss(content_output, content_target)
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  content_loss *= content_weight / num_content_layers

  loss = style_loss + content_loss
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```

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  style_loss *= style_weight / num_style_layers

  content_loss = tf.add_n([get_content_loss(content_output, content_target)
                  for content_output, content_target in zip(content_outputs, content_targets)])
  content_loss *= content_weight / num_content_layers

  loss = style_loss + content_loss
  return loss
```

```
def calculate_gradients(image, content_targets,
                        style_targets, style_weight,
                        content_weight,with_regularization=False):

    with tf.GradientTape() as tape:
        style_features = get_style_image_features(image)
        content_features = get_content_image_features(image)
        loss = get_style_content_loss(style_targets, style_features,
                                      content_targets, content_features,
                                      style_weight, content_weight)

    gradients = tape.gradient(loss, image)

    return gradients
```

```
def calculate_gradients(image, content_targets,
                        style_targets, style_weight,
                        content_weight,with_regularization=False):

    with tf.GradientTape() as tape:
        style_features = get_style_image_features(image)
        content_features = get_content_image_features(image)
        loss = get_style_content_loss(style_targets, style_features,
                                      content_targets, content_features,
                                      style_weight, content_weight)

    gradients = tape.gradient(loss, image)

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        style_features = get_style_image_features(image)
        content_features = get_content_image_features(image)
        loss = get_style_content_loss(style_targets, style_features,
                                      content_targets, content_features,
                                      style_weight, content_weight)

    gradients = tape.gradient(loss, image)

    return gradients
```

```
def update_image_with_style(image, content_targets, style_targets,
                            optimizer, style_weight, content_weight,
                            with_regularization=False):

  gradients = calculate_gradients(image, content_targets,
                                  style_targets, style_weight,
                                  content_weight,with_regularization)

  optimizer.apply_gradients([(gradients, image)]) #Apply gradients on image
```

```
def update_image_with_style(image, content_targets, style_targets,
                            optimizer, style_weight, content_weight,
                            with_regularization=False):

  gradients = calculate_gradients(image, content_targets,
                                  style_targets, style_weight,
                                  content_weight,with_regularization)

  optimizer.apply_gradients([(gradients, image)]) #Apply gradients on image
```

```
def update_image_with_style(image, content_targets, style_targets,
                            optimizer, style_weight, content_weight,
                            with_regularization=False):

  gradients = calculate_gradients(image, content_targets,
                                  style_targets, style_weight,
                                  content_weight,with_regularization)

  optimizer.apply_gradients([(gradients, image)]) #Apply gradients on image
```

```
def fit_style_transfer(input_image, style_image, optimizer,
                       epochs=1, steps_per_epoch=1,
                       with_regularization=False, style_weight = 0.01):


  for n in range(epochs):
    for m in range(steps_per_epoch):
         update_image_with_style(input_image, content_targets,
                                 style_targets, optimizer,
                                 style_weight, content_weight,
                                with_regularization=with_regularization)

  return input_image, images
```

Visualizing Outputs - Final Results

Style Image

https://upload.wikimedia.org/wikipedia/commons/b/b4/Vassily_Kandinsky%2C_1913_-_Composition_7.jpg

Content Image

https://cdn.pixabay.com/photo/2017/02/28/23/00/swan-2107052_1280.jpg

Stylized Image

Style Loss

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{i,j}^l - A_{ij}^l)^2$$

l: layer *l*

$\mathbf{A}^l_{ij}$: Style Representation(Gram Matrix) of style image a.

$\mathbf{G}^l_{ij}$: Style Representation(Gram Matrix) of generated image x

Gram Matrix

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l}$$

G_{ij}^{l}: inner product between vectorized feature maps i and j in layer l.

http://mlwiki.org/index.php/Gram_Matrices

Style Loss (one layer)

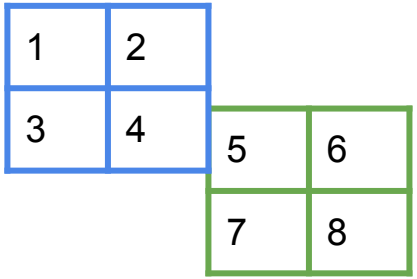
Style layer

H
W
F

Style Loss (one layer)

Style layer

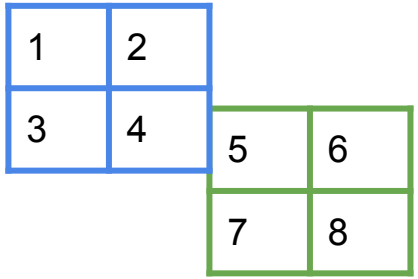
H =2
W = 2
F = 2

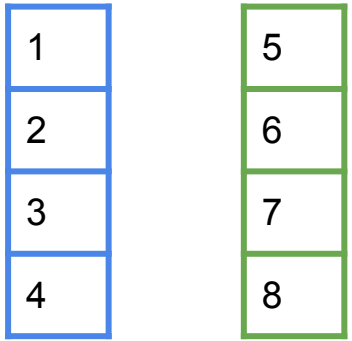


Style Loss (one layer)

Style layer

H =2
W = 2
F = 2

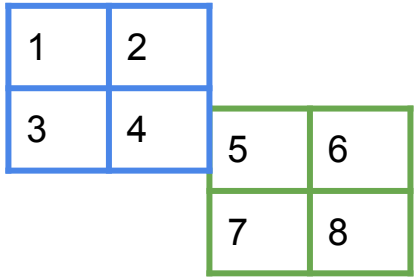




Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



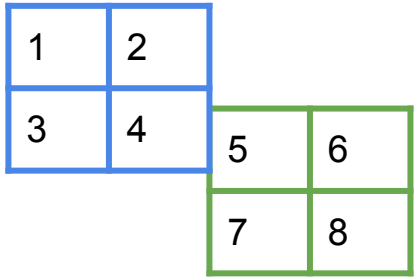
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix}$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



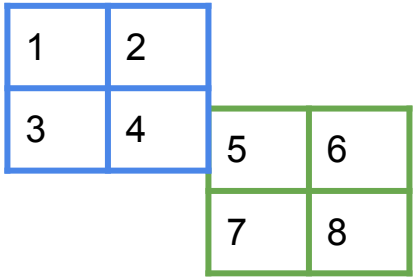
$$A = \left[\begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} \quad \begin{matrix} 5 \\ 6 \\ 7 \\ 8 \end{matrix} \right] \quad G = \left[\quad \right]$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



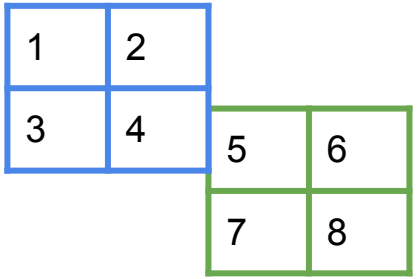
$$A = \left[\begin{array}{cc} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{array}\right] \quad G = \left[\begin{array}{cc} a_1 \cdot a_1 & \\ & \end{array}\right]$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



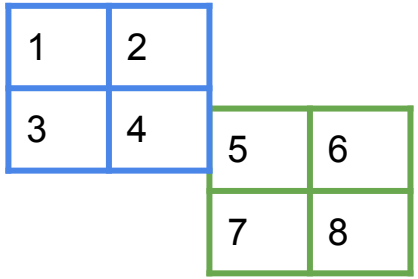
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \end{bmatrix}$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



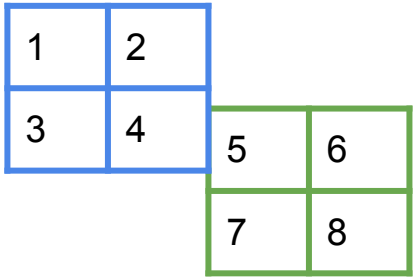
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} \quad G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \\ a_2 \cdot a_1 & \end{bmatrix}$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



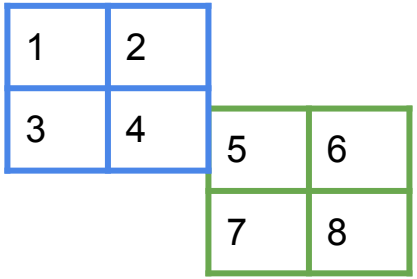
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} \quad G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \\ a_2 \cdot a_1 & a_2 \cdot a_2 \end{bmatrix}$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



Gram matrix

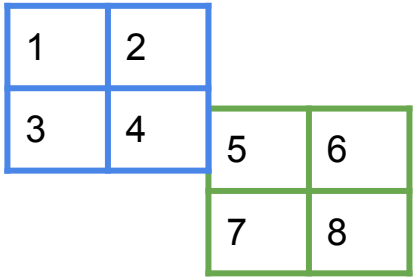
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} \quad G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \\ a_2 \cdot a_1 & a_2 \cdot a_2 \end{bmatrix}$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



Gram matrix

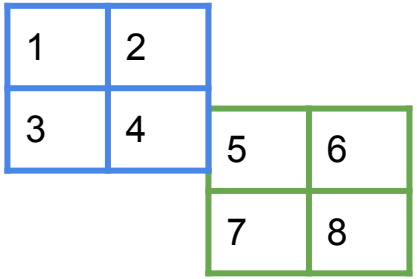
$$A = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} \quad G = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 \\ a_2 \cdot a_1 & a_2 \cdot a_2 \end{bmatrix} = A^T A$$

a_1 a_2

Style Loss (one layer)

Style layer

H =2
W = 2
F = 2



Gram matrix

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

a_1 a_2

Style feature

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))


A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

```
[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))


A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
AT = tf.transpose(A)
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]

[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

```
A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

```
AT = tf.transpose(A)
```

```
[[1, 2, 3, 4],
 [5, 6, 7, 8]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

```
A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

```
AT = tf.transpose(A)
```

```
[[1, 2, 3, 4],
 [5, 6, 7, 8]]
```

```
G = tf.matmul(AT,A)
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

```
A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

```
AT = tf.transpose(A)
```

```
[[1, 2, 3, 4],
 [5, 6, 7, 8]]
```

```
G = tf.matmul(AT,A)
```

```
[[ 30,  70],
 [ 70, 174]]
```

Style Loss (code)

```
style_layer = tf.constant([1,2,3,4,5,6,7,8],
                          shape=(2,2,2))
```

```
[[[1, 2],
  [3, 4]],

 [[5, 6],
  [7, 8]]]
```

```
A = tf.transpose(
        tf.reshape(style_layer,
                   shape=(2,4)))
```

```
[[1, 5],
 [2, 6],
 [3, 7],
 [4, 8]]
```

```
AT = tf.transpose(A)
```

```
[[1, 2, 3, 4],
 [5, 6, 7, 8]]
```

```
G = tf.matmul(AT,A)
```

```
[[ 30,  70],
 [ 70, 174]]
```

```
G = tf.linalg.einsum('cij,dij->cd',
                     style_layer,
                     style_layer)
```

Einstein notation

`tf.linalg.einsum`

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

 xT = tf.transpose(x)
```

```
[1, 2],
[3, 4]
```

```
[1, 3],
[2, 4]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

 xT = tf.transpose(x)

 tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

 xT = tf.transpose(x)

 tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

 xT = tf.transpose(x)

 tf.linalg.einsum('ij,ij->ij', x, x)

 tf.square(x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

xT = tf.transpose(x)

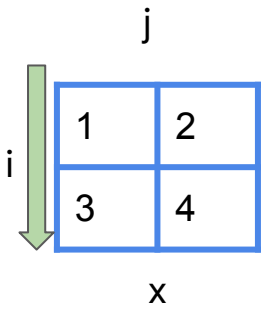
tf.linalg.einsum('ij,ij->ij', x, x)

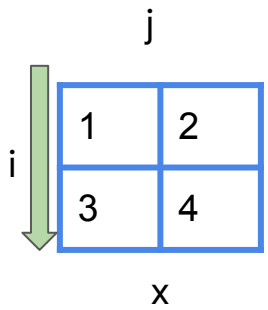
tf.square(x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```





Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

xT = tf.transpose(x)

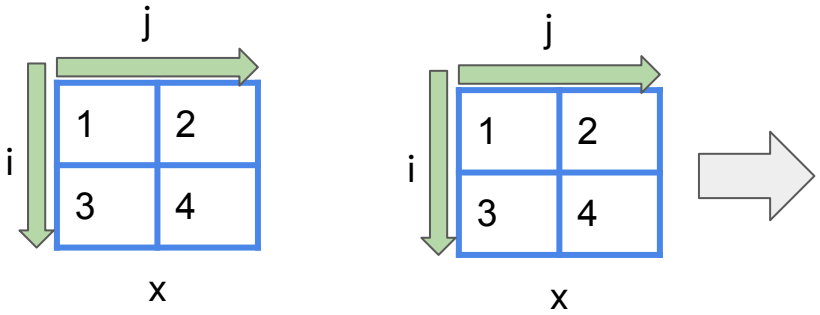
tf.linalg.einsum('ij,ij->ij', x, x)

tf.square(x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```



Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

xT = tf.transpose(x)

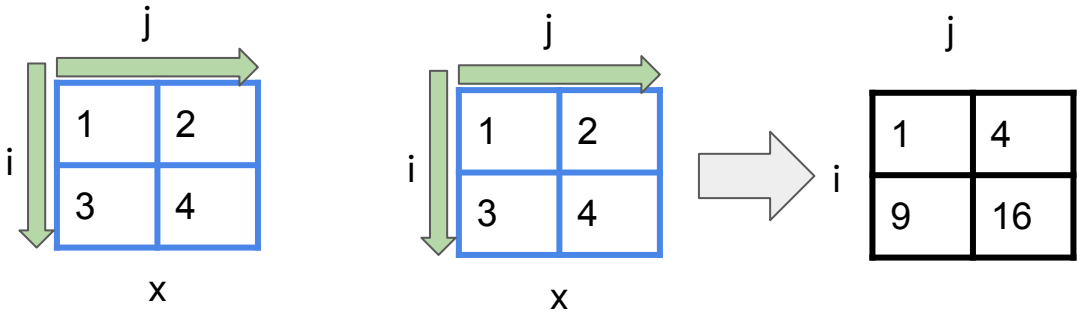
tf.linalg.einsum('ij,ij->ij', x, x)

tf.square(x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```



Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

 xT = tf.transpose(x)

 tf.linalg.einsum('ij,ij->ij', x, x)

 tf.square(x)

 tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[ 1,  4],
[ 9, 16]
```

```
tf.square(x)
```

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[ 1,  4],
[ 9, 16]
```

```
tf.square(x)
```

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

```
tf.matmul(xT, x)
```

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))

xT = tf.transpose(x)

tf.linalg.einsum('ij,ij->ij', x, x)

tf.square(x)

tf.linalg.einsum('ij,jk->ik', xT, x)

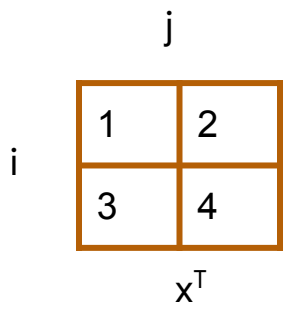
tf.matmul(xT, x)
```

```
[1, 2],
[3, 4]

[1, 3],
[2, 4]

[ 1,  4],
[ 9, 16]

[10, 14],
[14, 20]
```



Einstein notation

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x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[ 1,  4],
[ 9, 16]
```

```
tf.square(x)
```

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

```
tf.matmul(xT, x)
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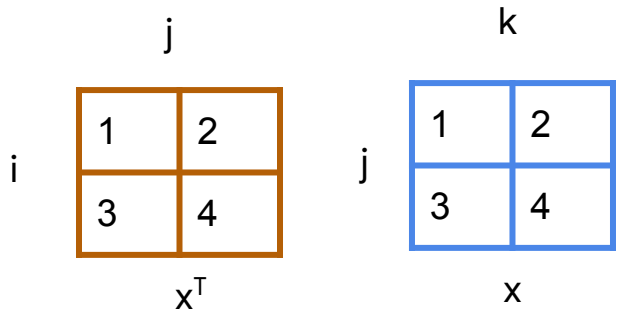

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[ 1,  4],
[ 9, 16]
```

```
tf.square(x)
```

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

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[10, 14],
[14, 20]
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tf.matmul(xT, x)
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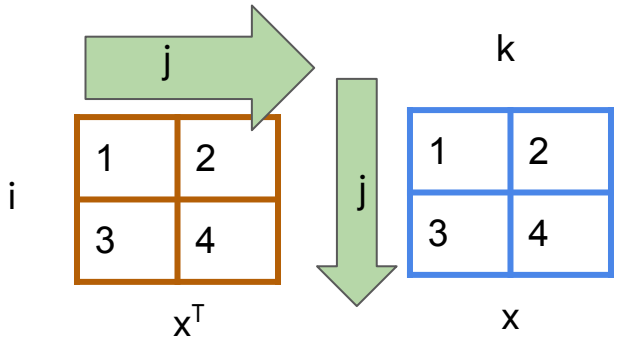

Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

```
[ 1,  4],
[ 9, 16]
```

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tf.square(x)
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```
tf.linalg.einsum('ij,jk->ik', xT, x)
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```
[10, 14],
[14, 20]
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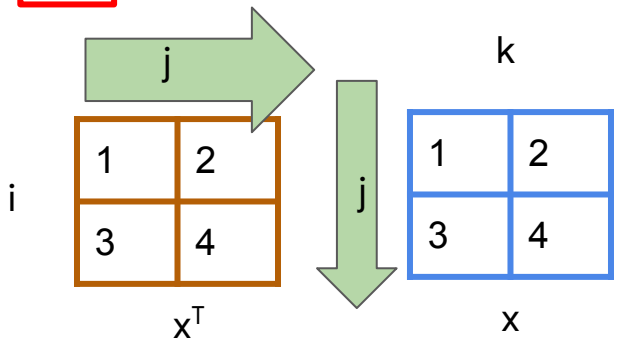
tf.matmul(xT, x)
```



Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
xT = tf.transpose(x)
```

```
[1, 3],
[2, 4]
```

```
tf.linalg.einsum('ij,ij->ij', x, x)
```

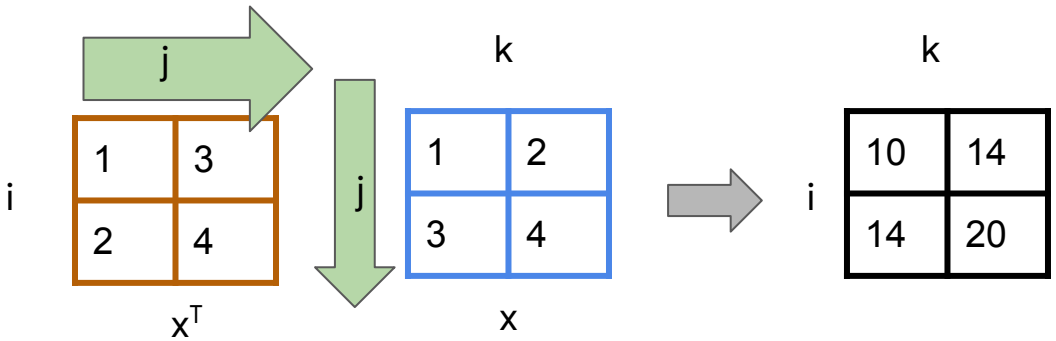
```
[ 1,  4],
[ 9, 16]
```

```
tf.square(x)
```

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

```
tf.matmul(xT, x)
```



Reduce sum

Reduce sum

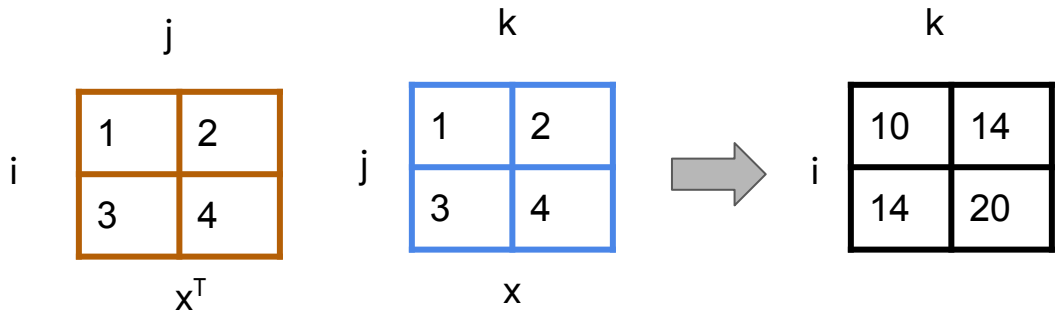
```
tf.linalg.einsum('ij,jk->ik , xT, x)
```

```
[10, 14],
[14, 20]
```

Reduce sum

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

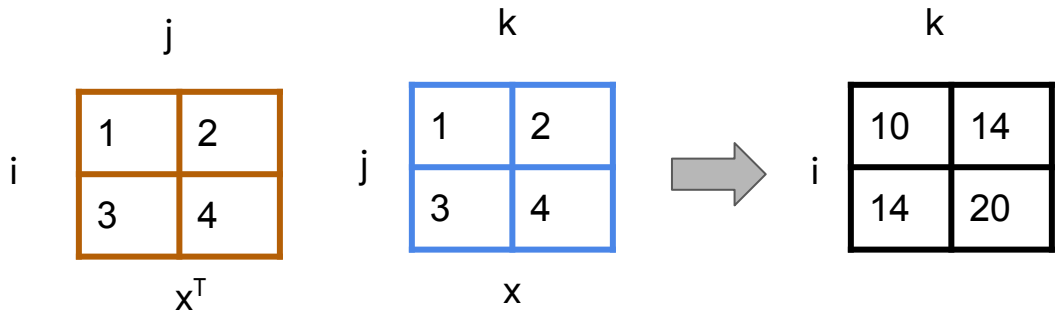



```
tf.linalg.einsum('ij,jk->', xT, x)
```

Reduce sum

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```

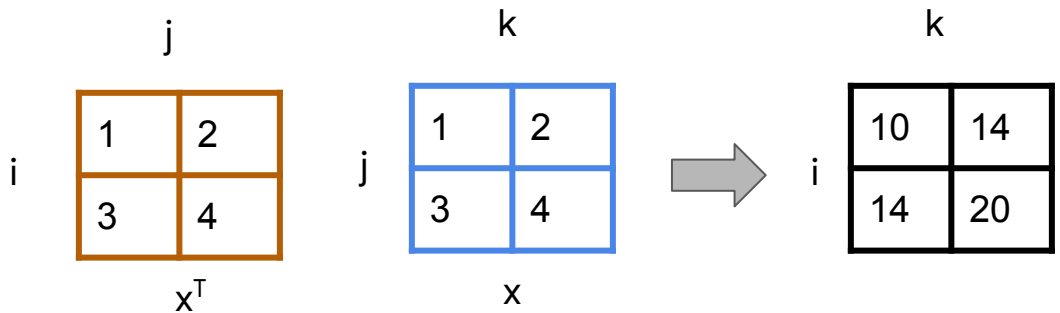



```
tf.linalg.einsum('ij,jk->', xT, x)
```

Reduce sum

```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```



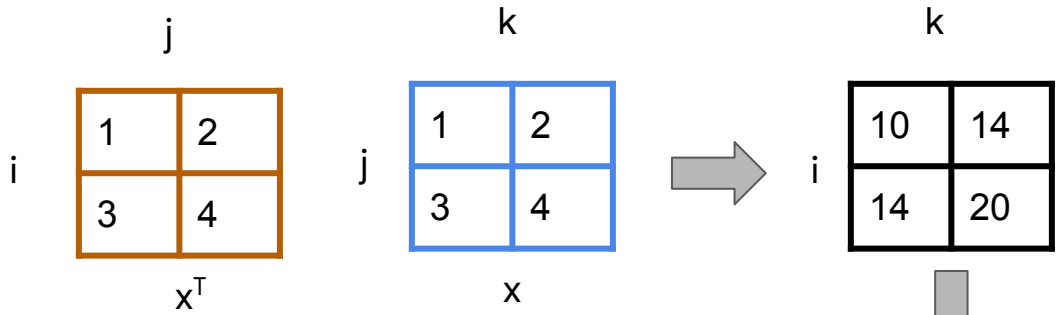

```
tf.linalg.einsum('ij,jk->', xT, x)
```

```
[58]
```

Reduce sum

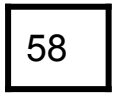
```
tf.linalg.einsum('ij,jk->ik', xT, x)
```

```
[10, 14],
[14, 20]
```




```
tf.linalg.einsum('ij,jk->', xT, x)
```

```
[58]
```



Einstein notation

```
x = tf.constant([1,2,3,4],shape=(2,2))
```

```
[1, 2],
[3, 4]
```

```
 v = tf.reshape(x, shape=(4,1) )
```

```
[1,
 2,
 3,
 4]
```

```
vT = tf.transpose(v)
```

```
[1,2,3,4]
```

```
tf.matmul(vT,v)
```

```
[30]
```

```
tf.linalg.einsum('ij,ij->', x, x)
```

```
[30]
```

Style Loss

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} (G_{i,j}^l - A_{ij}^l)^2$$

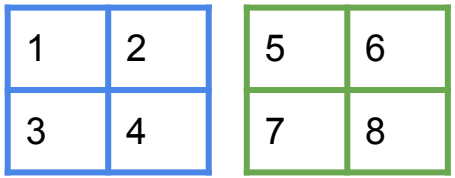
l: layer *l*

$\mathbf{A}^l_{ij}$: Style Representation(Gram Matrix) of style image a.

$\mathbf{G}^l_{ij}$: Style Representation(Gram Matrix) of generated image x)

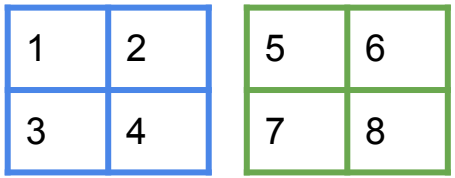
Weighting the style loss

Style layer (height, width, filters)



Weighting the style loss

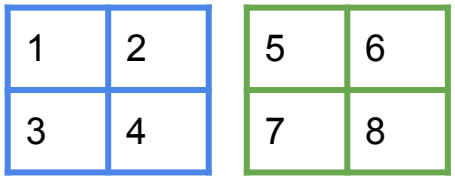
Style layer (height, width, filters)



Height =2
Width = 2
Filters = 2

Weighting the style loss

Style layer (height, width, filters)



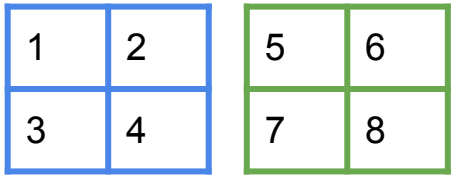
Height =2
Width = 2
Filters = 2

Style weight

$$\frac{1}{(2 \times h \times w \times f)^2}$$

Weighting the style loss

Style layer (height, width, filters)



Height =2
Width = 2
Filters = 2

Style weight

$$\frac{1}{(2 \times h \times w \times f)^2}$$

$$E_l = \frac{1}{4 N_l^2 M_l^2} \sum_{i,j} (G_{i,j}^l - A_{ij}^l)^2$$

Gram Matrix - In Practice

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
  result = tf.linalg.einsum('bijc,bijd->bcd' input_tensorT, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

https://numpy.org/doc/stable/reference/generated/numpy.einsum.html

Gram Matrix - In Practice

(batch, height, width, filters)

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
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```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

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```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

b b

```
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  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensorT, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

b i j b

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensorT, input_tensor)
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Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

b i j b i j

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```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

b i j c b i j

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensorT, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters)

b i j c b i j d

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensorT, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters) (batch, filters, filters)

b i j c b i j d b c d

```
def gram_matrix(input_tensor):
  input_tensorT = tf.transpose(input_tensor,perm[0,2,1,3])
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  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Gram Matrix - In Practice

(batch, height, width, filters) (batch, height, width, filters) (batch, filters, filters)

b i j c b i j d b c d

```
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  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

https://numpy.org/doc/stable/reference/generated/numpy.einsum.html

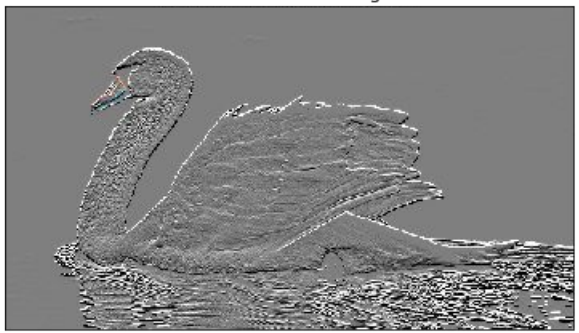
Extract High Frequency Components

```
def high_pass_x_y(image):
  x_var = image[:,:,1:,:] - image[:,:,:-1,:]
  y_var = image[:,1:,:,:] - image[:,:-1,:,:]

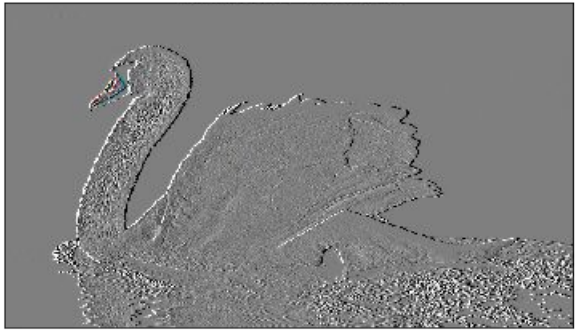
  return x_var, y_var
```

Visualization-High Frequency Artifacts

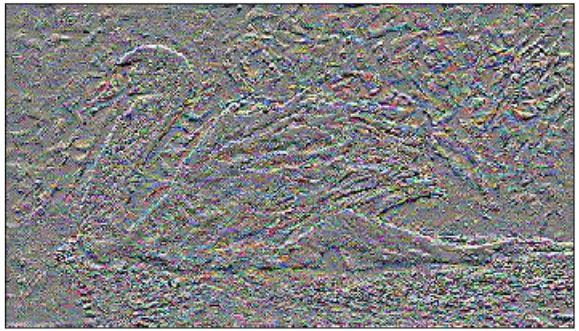
Horizontal Deltas: Original



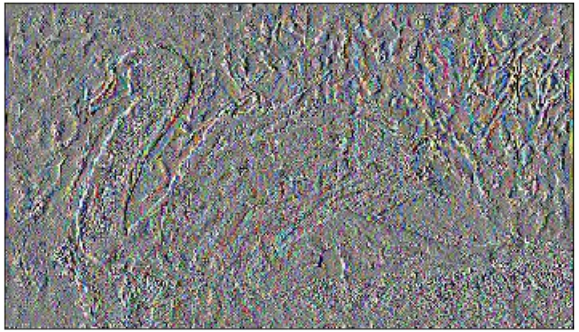
Vertical Deltas: Original



Horizontal Deltas: Stylized Image



Vertical Deltas: Stylized Image



Solution - Total Variation Loss

- Decrease high frequency artefacts.
- Explicit regularization term on high frequency components

Factoring in Total Variation using TensorFlow

```
loss += total_variation_weight * tf.image.total_variation(image)
```

```
def calculate_gradients(image, content_targets,
                        style_targets, style_weight,
                        content_weight,with_regularization=False ):

    total_variation_weight = 30
    with tf.GradientTape() as tape:
      if with_regularization:
        loss += total_variation_weight*tf.image.total_variation(image)

    gradients = tape.gradient(loss, image)
    return gradients
```

```
def calculate_gradients(image, content_targets,
                        style_targets, style_weight,
                        content_weight,with_regularization=False ):

    total_variation_weight = 30
    with tf.GradientTape() as tape:
      if with_regularization:
        loss += total_variation_weight*tf.image.total_variation(image)

    gradients = tape.gradient(loss, image)
    return gradients
```

Comparison

Without Variation Loss

With Variation Loss

https://cdn.pixabay.com/photo/2017/02/28/23/00/swan-2107052_1280.jpg

https://arxiv.org/pdf/1705.06830.pdf

Exploring the structure of a real-time, arbitrary neural artistic stylization network

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August 28, 2017

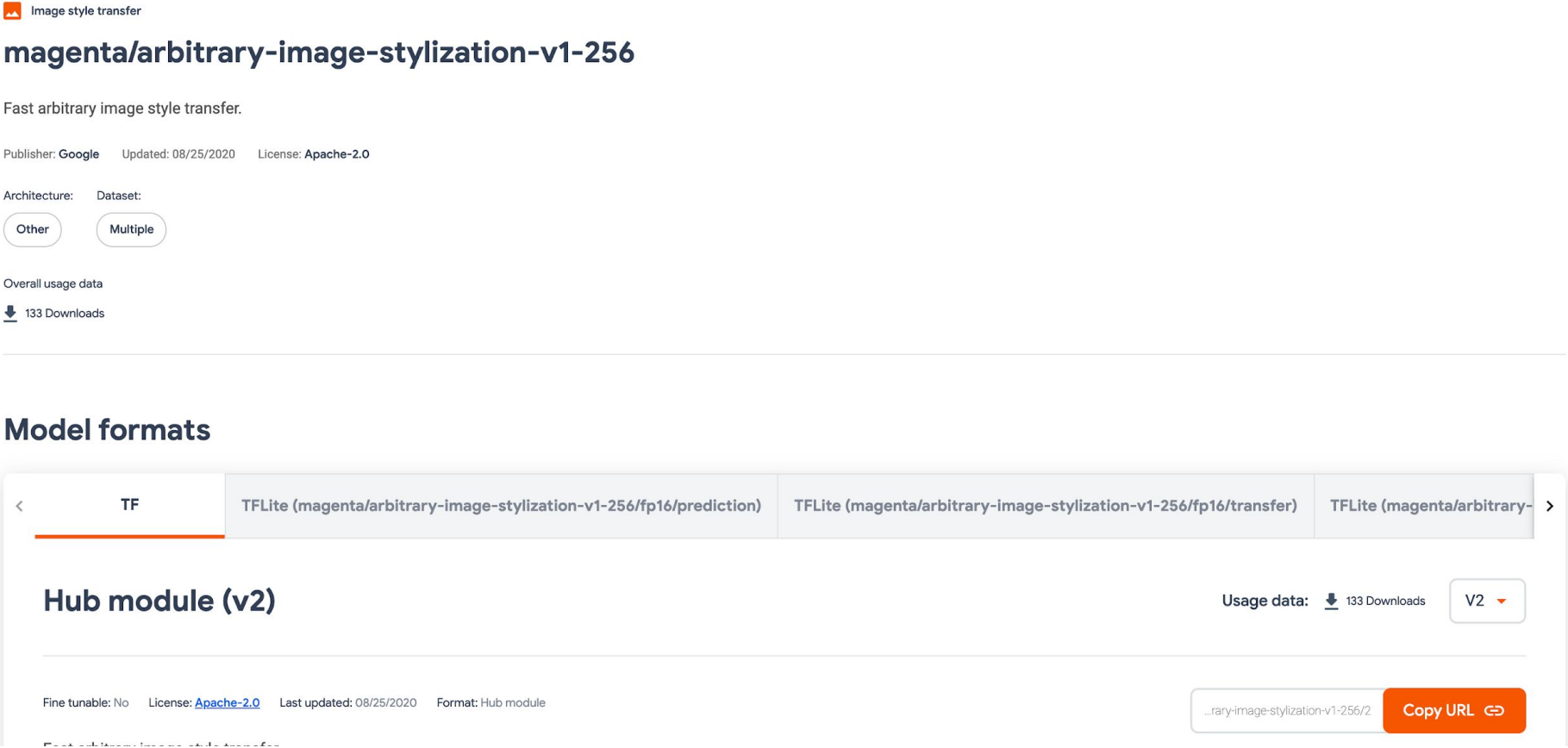
Abstract

In this paper, we present a method which combines the flexibility of the neural algorithm of artistic style with the speed of fast style transfer networks to allow real-time stylization using any content/style image pair. We build upon recent work leveraging conditional instance normalization for multi-style transfer networks by learning to predict the conditional instance normalization parameters directly from a style image. The model is successfully trained on a corpus of roughly 80,000 paintings and is able to generalize to paintings previously unobserved. We demonstrate that the learned embedding space is smooth and contains a rich structure and organizes semantic information associated with paintings in an entirely unsupervised manner.

1 Introduction

Elmyr de Hory gained world-wide fame by forging thousands of pieces of artwork and selling them to art dealers and museums [13]. The forger's skill is a testament to the human talent and intelligence required to reproduce the artistic details of a diverse set of paintings. In computer vision, much work has been invested in teaching computers to likewise capture the artistic style of a painting with the goal of conferring this style in arbitrary photographs in a convincing manner.

https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2



```
import tensorflow_hub as hub

h_m = hub.load
        ('https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2')
```

```
import tensorflow_hub as hub

h_m = hub.load
        ('https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2')


content_image, style_image = load_images("content.jpg", "style.jpg")
```

```
import tensorflow_hub as hub

h_m = hub.load
        ('https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2')

content_image, style_image = load_images("content.jpg", "style.jpg")

stylized_image = h_m(tf.image.convert_image_dtype(content_image, tf.float32),
                     tf.image.convert_image_dtype(style_image, tf.float32))[0]
```

```
import tensorflow_hub as hub

h_m = hub.load
        ('https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2')

content_image, style_image = load_images("content.jpg", "style.jpg")

stylized_image = h_m(tf.image.convert_image_dtype(content_image, tf.float32),
                     tf.image.convert_image_dtype(style_image, tf.float32))[0]

tensor_to_image(stylized_image)
```