

Artistic Style Transfer

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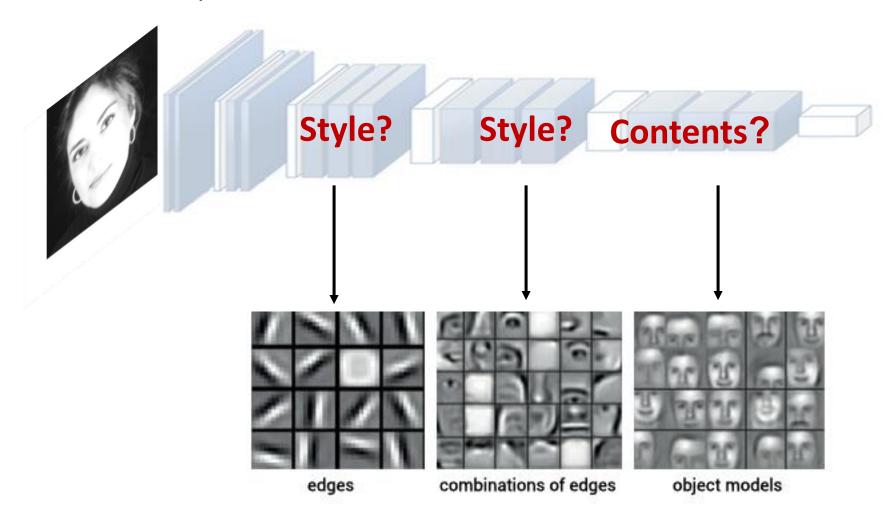
Artistic Style Transfer





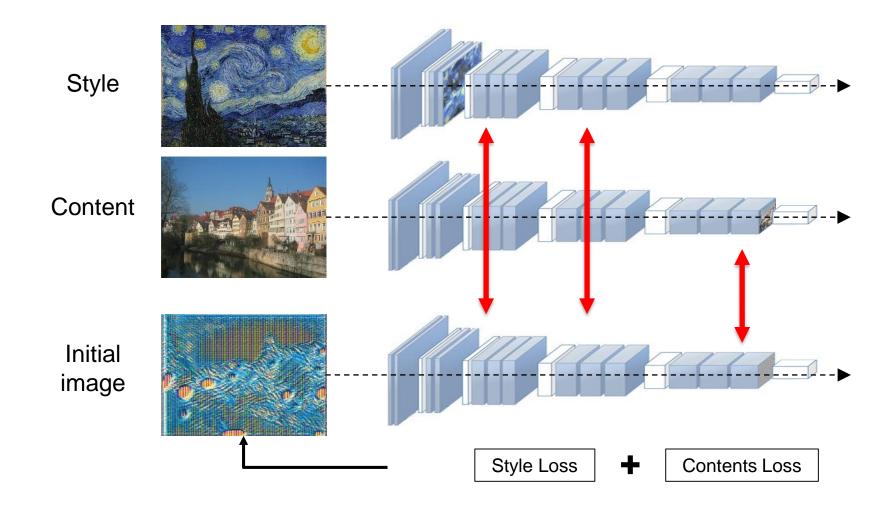
Convolutional NN

• Hierarchical feature representation





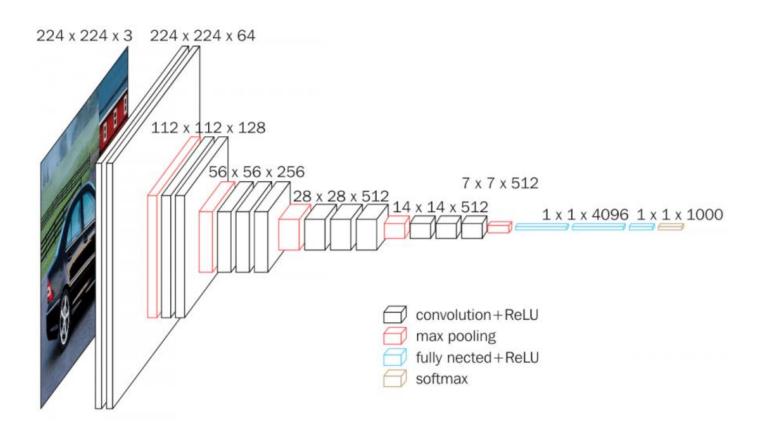
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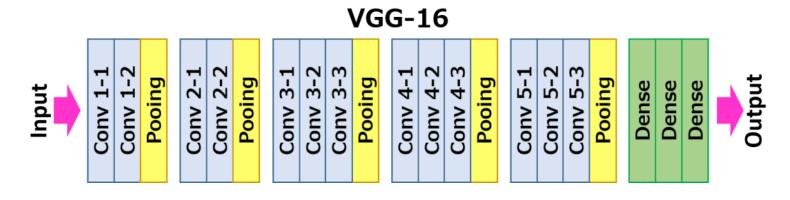




Implementation

• VGG16

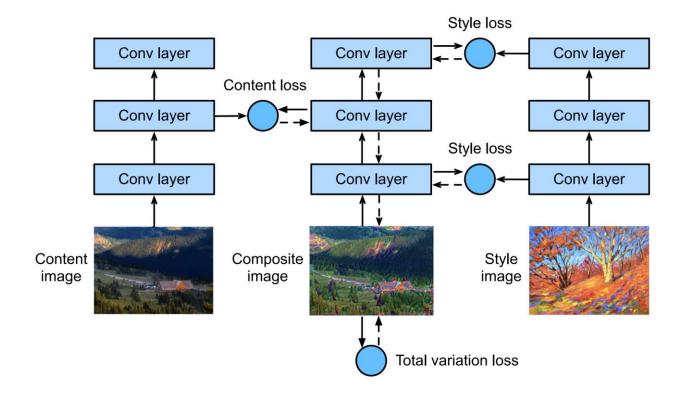






Implementation

- Composite image is the only variable that needs to be updated
- We select a pre-trained CNN to extract image features
- The output of certain layers to use as content features or style features





Implementation

 Content loss is used to make the composite image approximate the content image as regards content features

```
def get_loss_content(gen_layer, ref_layer):
   loss = tf.reduce_mean(tf.square(gen_layer - ref_layer))
   return loss
```

- Style loss is used to make the composite image approximate the style image in terms of style features
 - Gram matrix

```
def get_gram_matrix(conv_layer):
    channels = conv_layer.get_shape().as_list()[3]
    conv_layer = tf.reshape(conv_layer, (-1, channels))
    gram_matrix = tf.matmul(tf.transpose(conv_layer), conv_layer)
    return gram_matrix/((conv_layer.get_shape().as_list()[0])*channels)

def get_loss_style(gram_matrix_gen, gram_matrix_ref):
    loss = tf.reduce_mean(tf.square(gram_matrix_gen - gram_matrix_ref))
    return loss
```

Results







Total Variance Loss

- Sometimes, the composite images we learn have a lot of high-frequency noise, particularly bright or dark pixels.
- One common noise reduction method is total variation denoising.

$$\sum_{i,j} |x_{i,j} - x_{i+1,j}| + |x_{i,j} - x_{i,j+1}|$$

Results







