Image Style Transfer Using Convolutional Neural Networks

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Image Style Transfer

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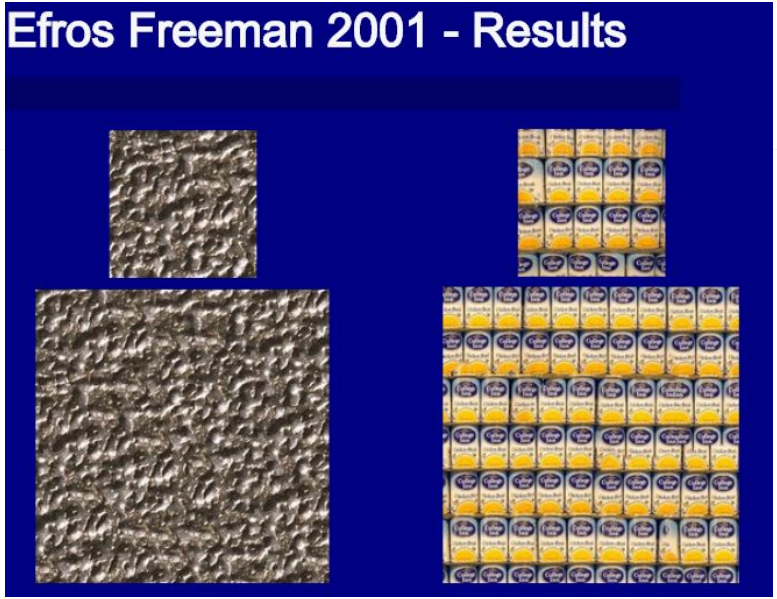
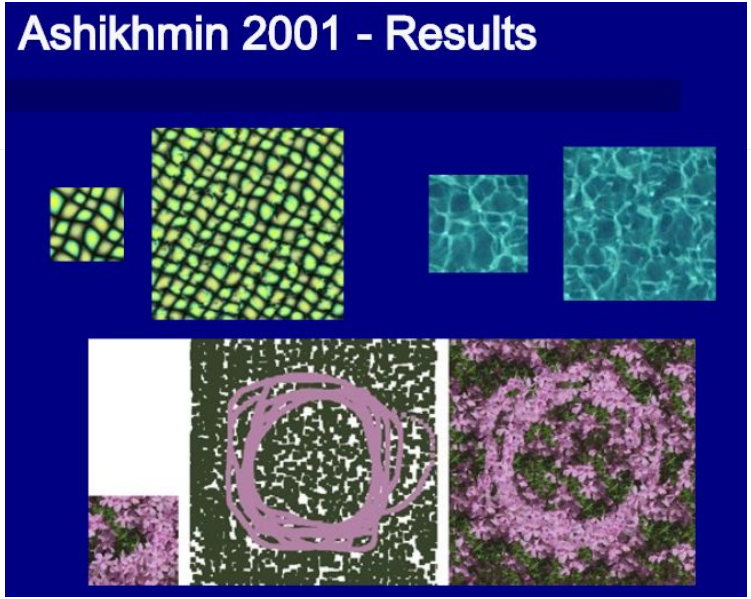
Older Methods of Texture Generation



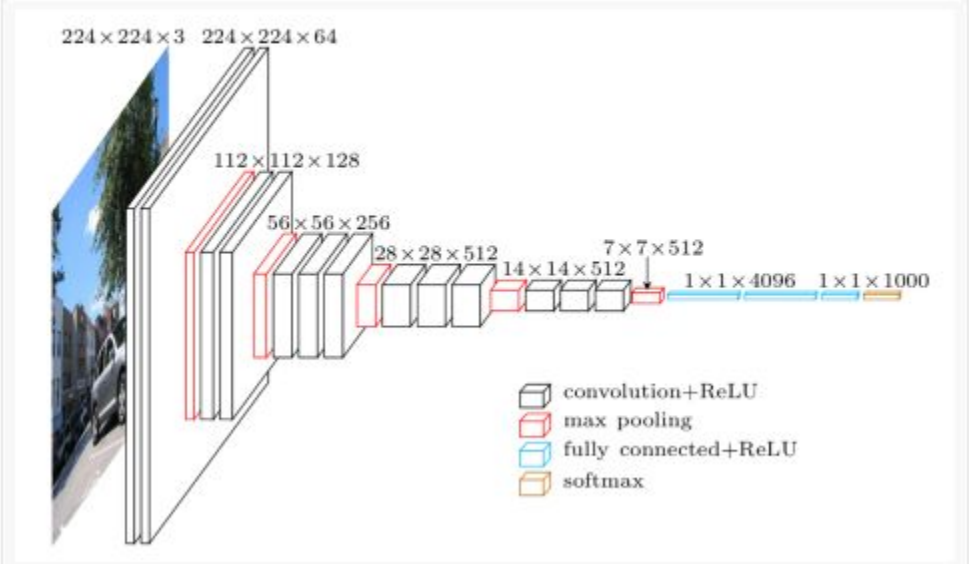
A.Efros, W. Freeman, Image Quilting for Texture Synthesis and Transfer, 2001



M. Ashikhmin, Synthesizing Natural Textures, 2001

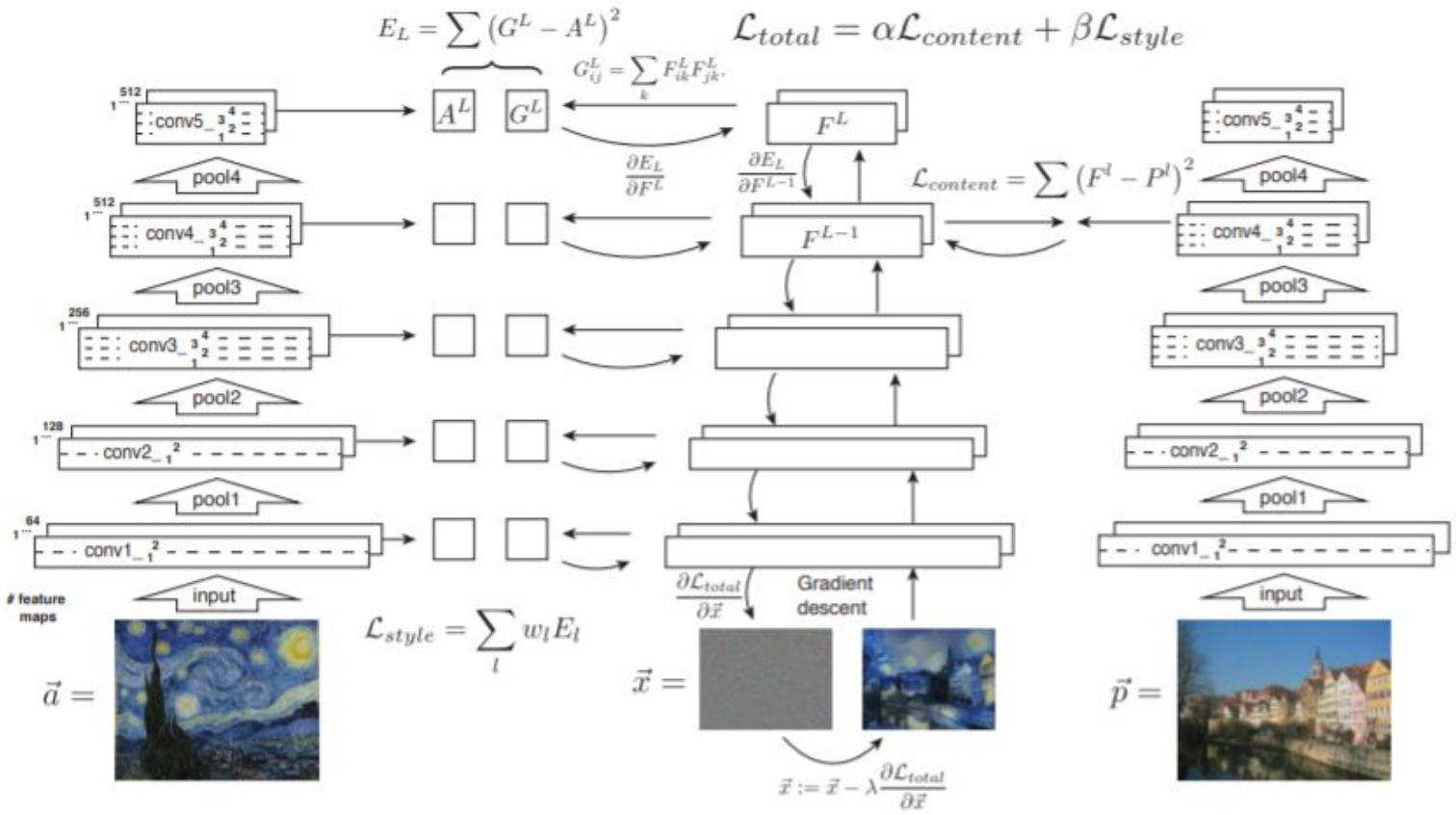
A VGG Network Was Used to Obtain Results

VGG16 and VGG19

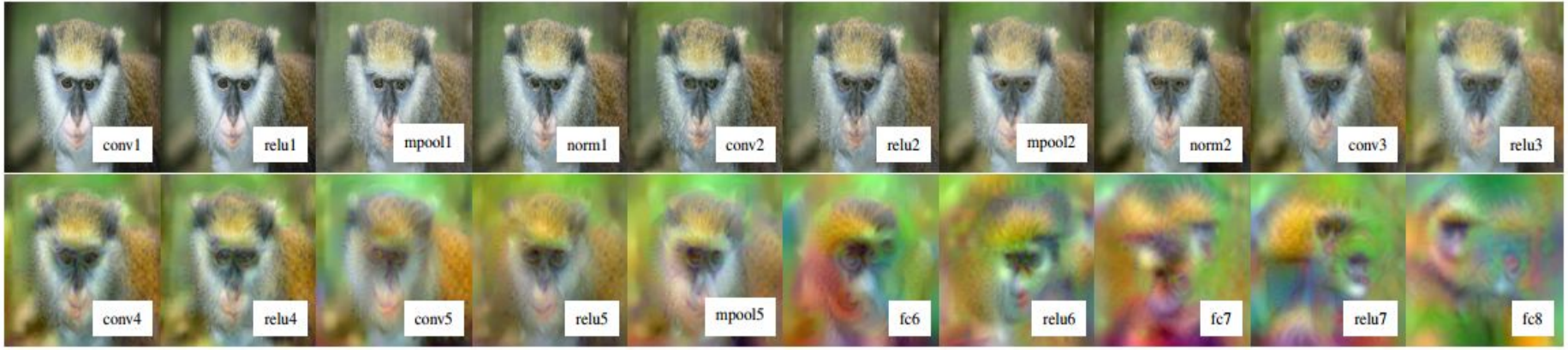


https://www.cs.toronto.edu/~frossard/post/vgg16/

Image Style Transfer Algorithm



Deep Image Representation



A. Mahendran and A. Vedaldi, "Understanding deep image representations by inverting them," *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, 2015, pp. 5188-5196.
doi: 10.1109/CVPR.2015.7299155

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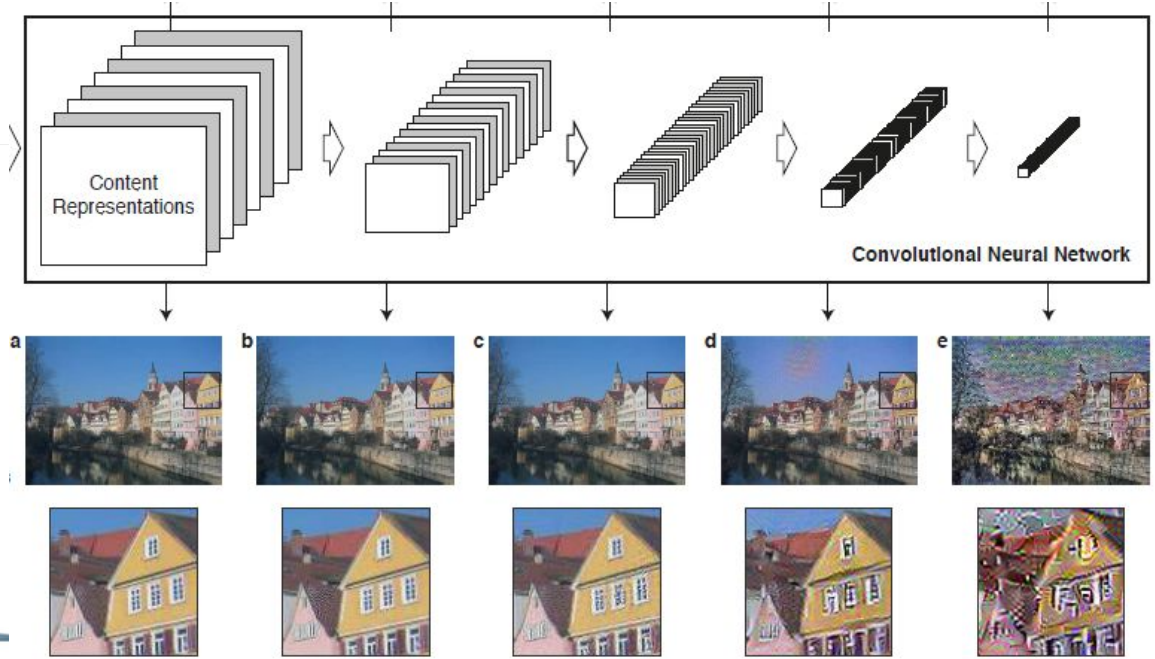
Higher Levels of the Network Preserve Semantic Content



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Content Representation

To visualize the image information at each layer, a gradient descent is performed on a white noise image to find another image that matches the feature response of the original.

Loss Function for Image Content

$$\mathcal{L}_{\text{content}}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} \left(F_{ij}^{l} - P_{ij}^{l}\right)^2$$

Derivative with Respect to Activations

$$\frac{\partial \mathcal{L}_{\text{content}}}{\partial F_{ij}^{l}} = \begin{cases} \left(F^{l} - P^{l}\right)_{ij} & \text{if } F_{ij}^{l} > 0 \\ 0 & \text{if } F_{ij}^{l} < 0 \,, \end{cases}$$

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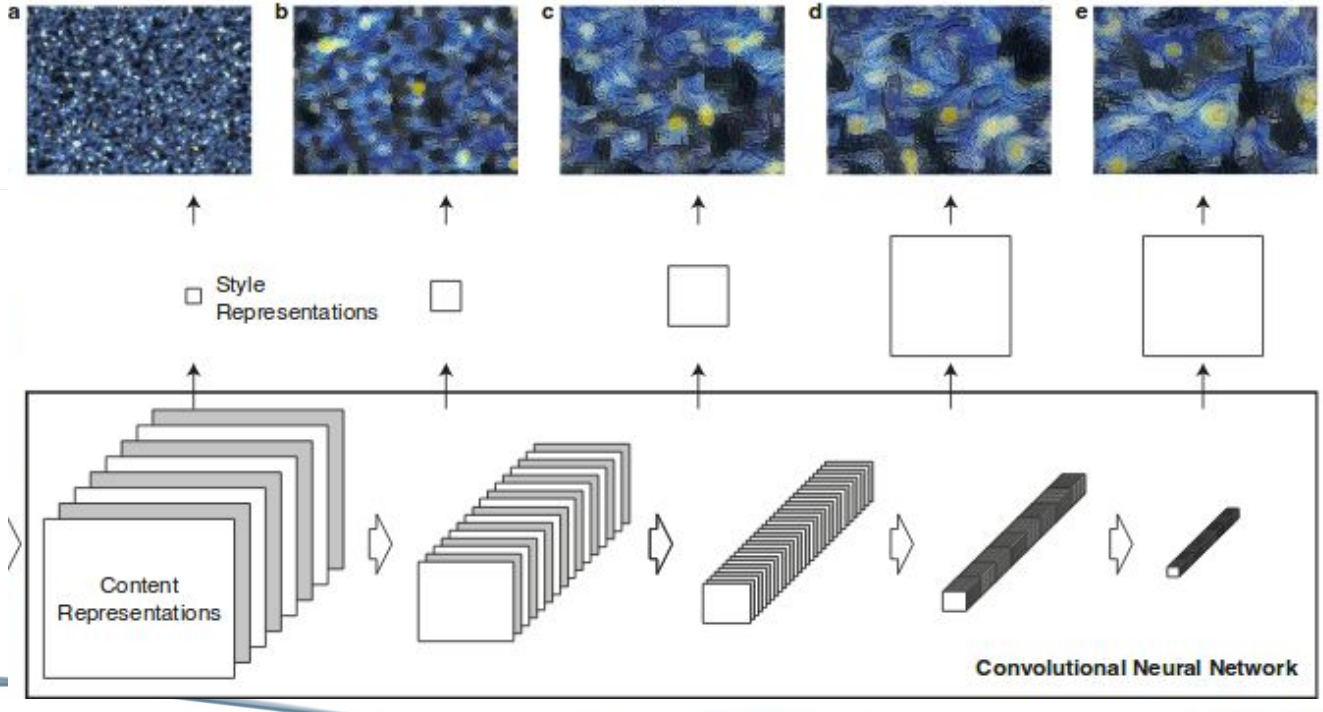
Style Representation



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Style Representation

- Compute activations @ desired layers
- Calculate Gram Matrices of activations

$$G(\mathbf{v}_1, \ldots, \mathbf{v}_k) = \begin{pmatrix} \langle \mathbf{v}_1, \mathbf{v}_1 \rangle & \cdots & \langle \mathbf{v}_1, \mathbf{v}_k \rangle \\ \vdots & & \vdots \\ \langle \mathbf{v}_k, \mathbf{v}_1 \rangle & \cdots & \langle \mathbf{v}_k, \mathbf{v}_k \rangle \end{pmatrix}.$$

- Style Loss function:

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

- Total Style Loss:

$$\mathcal{L}_{\text{style}}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l$$

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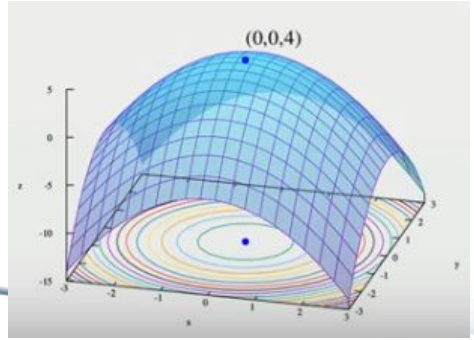
Training the Network

- Total Loss:

$$\mathcal{L}_{\text{total}}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{\text{content}}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{\text{style}}(\vec{a}, \vec{x})$$

- L-BFGS Optimization

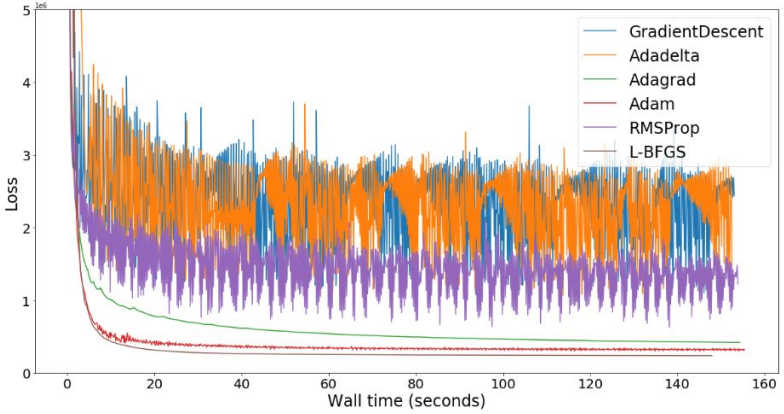


https://www.youtube.com/watch?v=1A6l0vcMNdc

Why L-BFGS?

Content image

Style image



Gradient Descent

Adadelta

RMSprop

Adam

Adagrad

L-BFGS

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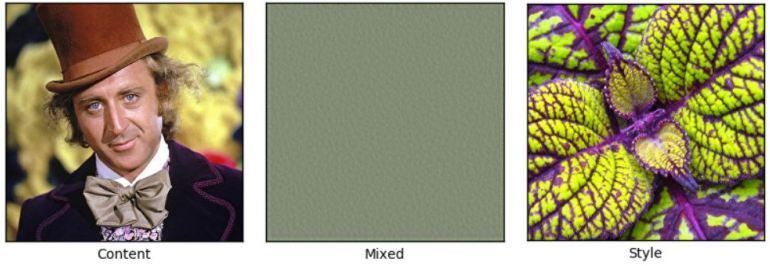
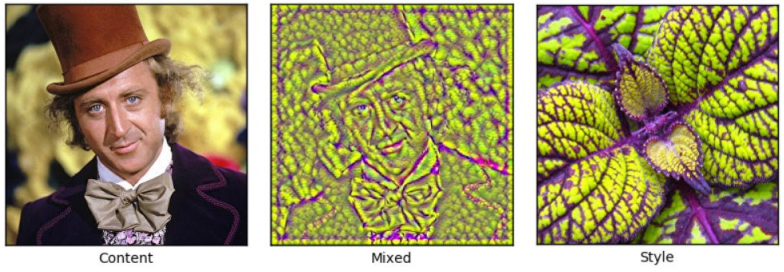
https://blog.slavv.com/picking-an-optimizer-for-style-transfer-86e7b8cba84b

Example

Iteration: 0
Weight Adj. for Content: 5.18e-11, Style: 2.14e-29, Denoise: 5.61e-06



Iteration: 10
Weight Adj. for Content: 2.79e-11, Style: 4.13e-28, Denoise: 1.25e-07



Iteration: 50
Weight Adj. for Content: 2.75e-11, Style: 1.12e-27, Denoise: 1.24e-07

Final image:

https://github.com/Hvass-Labs/TensorFlow-Tutorials/blob/master/15_Style_Transfer.ipynb

Style Matching vs. Content

$$\mathcal{L}_{\text{total}}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{\text{content}}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{\text{style}}(\vec{a}, \vec{x})$$

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Effect of Different Layers for Content

- Lower layers vs. Higher Layers
- Fine Structure vs. Style Blending

$(\alpha/\beta = 1 \times 10^{-3})$

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Discussion

Strengths

- New process of image generation combining features of 2 images from different layers of a CNN
- “I don’t care what it was designed to do, I care about what it can do”

Weaknesses

- System is not perfect, photorealism is still a hard area to handle
- Can be used to create fake content
- Resolution is limited (better in more recent examples)

Photorealistic Image Style Transfers

Original photo | Reference photo | Result

https://phys.org/news/2017-05-cornell-cis-adobe-collaboration-artificial.html

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Future Research

- Removing noise to achieve photorealistic image transfers
- Artistic outlets for creativity

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Thank You

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