

Fast Patch-based Style Transfer of Arbitrary Style

Tian Qi Chen and Mark Schmidt

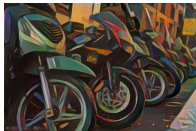
University of British Columbia



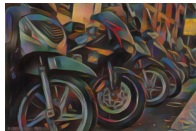
Content



Style



Our Method



Our Fast Approx.

Artistic Style Transfer

Combining a picture with Vincent van Gogh's *The Starry Night*:



Artistic Style Transfer

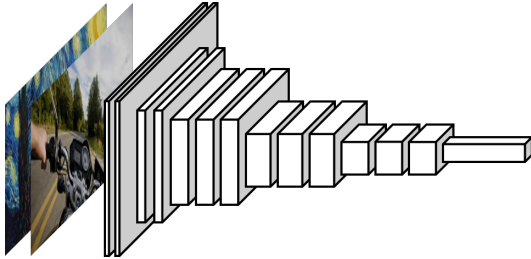
Combining a picture with Vincent van Gogh's *The Starry Night*:



A painting takes days to complete.

Can a computer be used to transfer the style of a painting onto another image?

Visual Quality comes from use of Convolutional Neural Nets



Processing at pixel level $\longrightarrow$ Processing at the **activations** level



Success in visual quality has created a market for mobile and web applications.

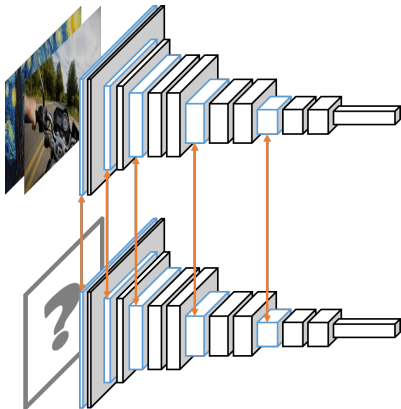
Existing Approaches: Optimization-based

How to define “style transfer”?

$$\arg \min_{\mathcal{I}} L(\mathcal{I}, \text{Content}, \text{Style})$$

Requires hundreds of forward and backward passes through the CNN.

Slow



e.g. Gatys et al. (2015), Li and Wand (2016)

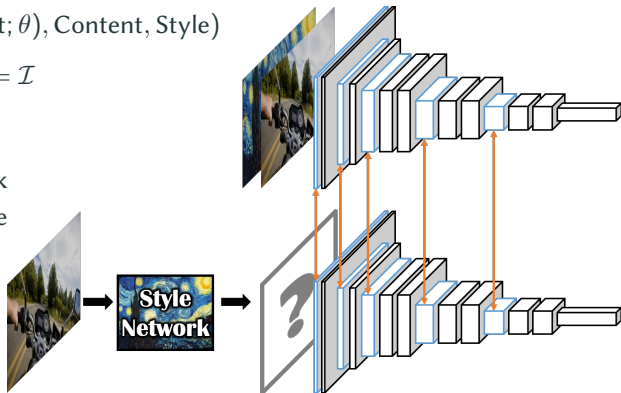
Existing Approaches: Feedforward Style Network

$$\min_{\theta} L(\text{StyleNet}(\text{Content}; \theta), \text{Content}, \text{Style})$$

$$\text{StyleNet}(\text{Content}; \theta^*) = \mathcal{I}$$

Train a neural network to approximate the optimization result.

Limited in Style



e.g. Ulyanov et al. (2016), Johnson et al. (2016), Dumoulin et al. (2016)

Motivation

Existing optimization-based approaches:

adaptable to any style image but slow

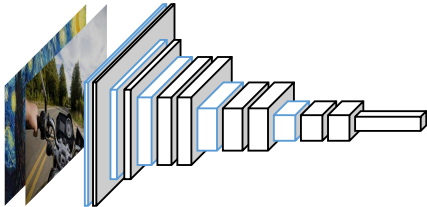
Existing feedforward approaches:

fast but limited

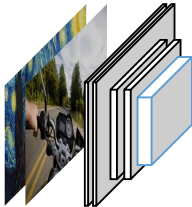
We present an approach that is:

feedforward, fast, and adaptable to any style image

Our Approach

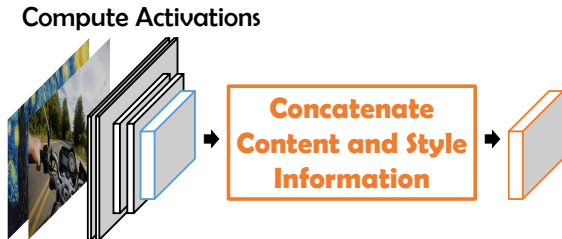


Our Approach



- restrict to the use of just a **single layer**

Our Approach



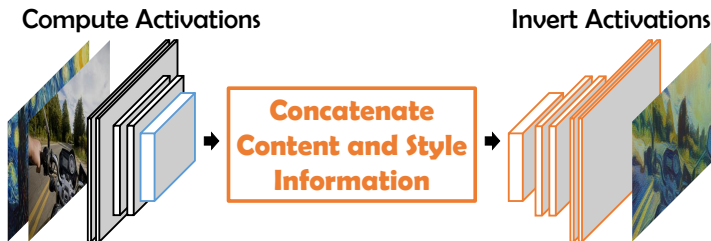
- restrict to the use of just a **single layer**
- directly **construct target activations**

Our Approach



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- directly **construct target activations**
- an **inverse network** that is not style-dependent

Our Approach



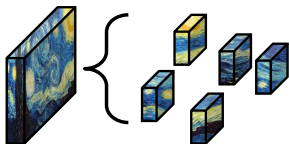
- restrict to the use of just a **single layer**
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- an **inverse network** that is not style-dependent

Differences from existing works:

- *Decoupling* of the style transfer process and image generation
- *Constructive procedure* instead of defining style transfer as an optimization

Patch-based Replacement (Style Swap)

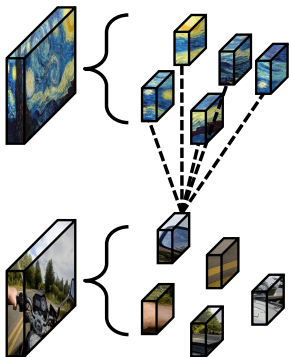
For every content patch, swap it with the **best matching** style patch.



Patch-based Replacement (Style Swap)

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$$\text{BestMatch}(c) = \arg \max_{s \in S} \frac{\langle c, s \rangle}{\|c\| \cdot \|s\|}$$

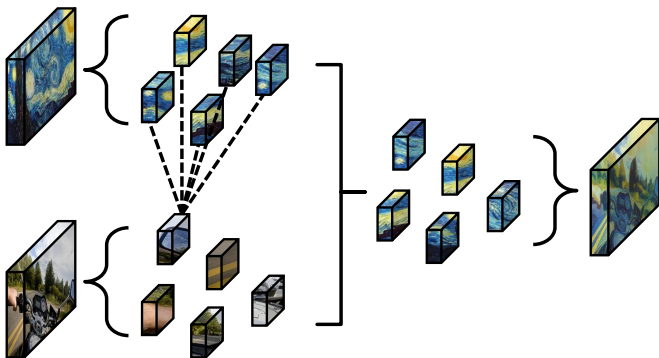


*(Li and Wand (2016) uses this measure, but inside an optimization procedure.)

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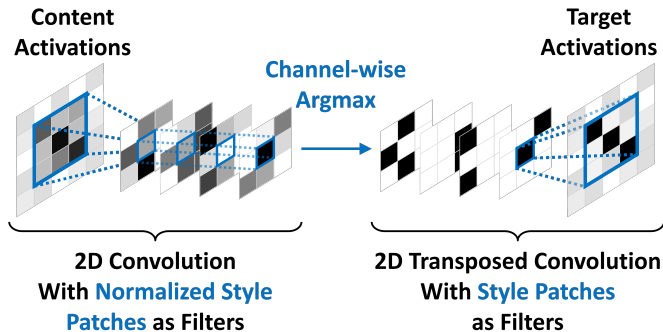


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Other names for the transposed convolution: fractionally-strided convolution, backward convolution, upconvolution, or “deconvolution”.

Properties of Style Swap: RGB vs. Activations



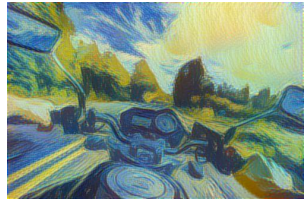
Content



Style



Style Swap RGB

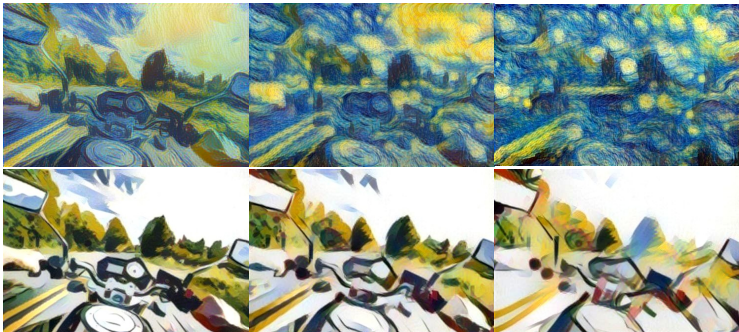


Style Swap Activations

Properties of Style Swap: Intuitive Tuning Parameter

Control **level of abstraction** using a single discrete parameter:

patch size.

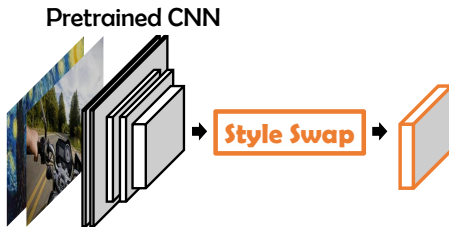


3×3 Patches

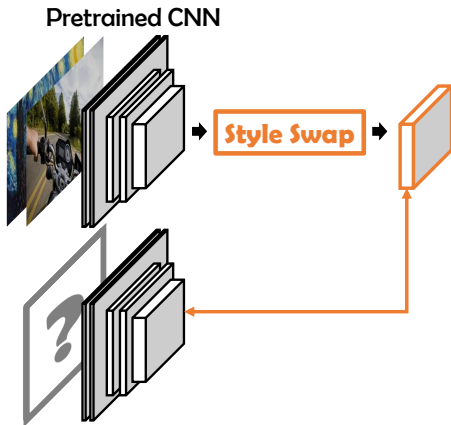
7×7 Patches

12×12 Patches

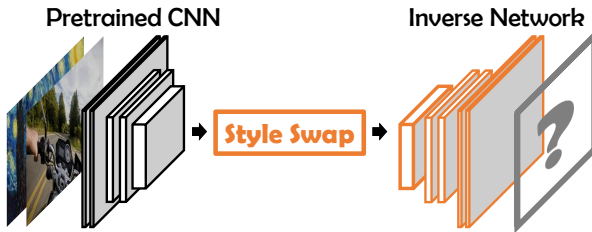
Inverting Activations: Option I



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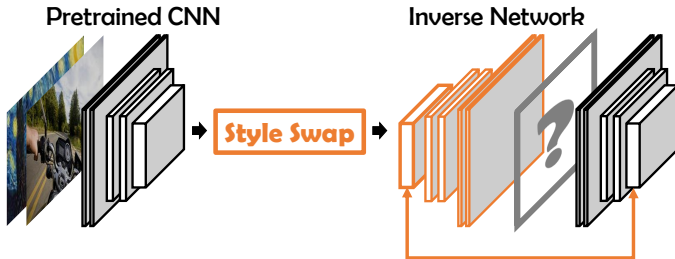
Inverting Activations: Option II



¹Microsoft COCO

²Painter by Numbers (public; hosted on [kaggle.com](https://www.kaggle.com))

Inverting Activations: Option II



We do unsupervised training of the inverse network.
We train using 80,000 photos¹ as content and 80,000 paintings² as style.

¹Microsoft COCO

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Computation Time

Comparison with existing methods that can handle [arbitrary style](#) images:

Method	N. Iters.	Time/Iter. (s)	Total (s)
Gatys et al.	500	0.1004	50.20
Li and Wand	200	0.6293	125.86
Style Swap (Optim)	100	0.0466	4.66
Style Swap (InvNet)	1	1.2483	1.25

Table 1: Computation time on 500×300 size images.

Computation Time

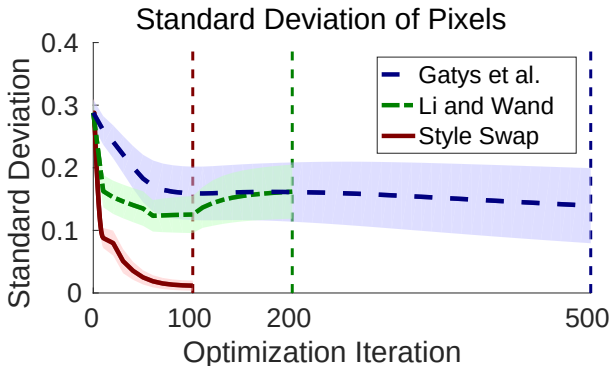
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Table 1: Computation time on 500×300 size images.

- Computation time for our method can be significantly reduced if number of style patches is reduced.
- Can scale to large content sizes if style image is kept at a manageable size.

Consistency: Few Local Optima



Empirically, we observe:

- Similar images → similar style transferred results.
- Consecutive frames of a video → consistent results.

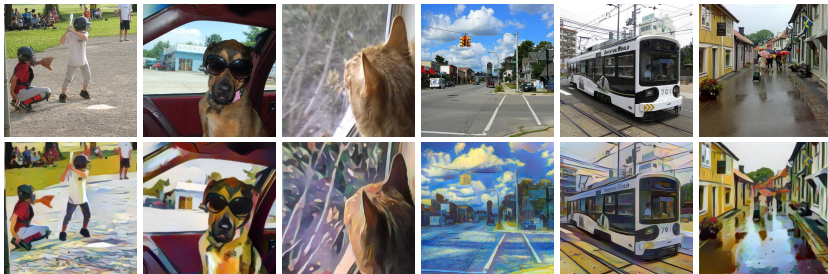
Frame-by-frame Application of Our Method

Timelapse Video of Vancouver, BC



Summary

- We present the first feedforward method for style transfer that can adapt to arbitrary style.
- Our method for style transfer has the following properties:
 - Tunable with a discrete intuitive tuning parameter
 - Consistent and allows frame-by-frame application to videos
 - Gives a degree of control over the style transfer result



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source code: github.com/rtqichen/style-swap