Task: redrawing any photo in the style of any painting.

- Artists take days or months to create a painting.
- Can a computer transfer the style of an image onto another?

The use of an auxiliary pretrained CNN improves visual quality.
But the current approaches are either slow (optimization-based) or limited in the number of styles (trained style network).
We present an approach that is both efficient and adaptable to any style.
We train on 80,000 natural images and 80,000 paintings.

We restrict to using only one layer of the pretrained CNN.
We isolate the stylizing process inside its own module.
The style-swapped activations can be inverted by either optimization or an inverse network.

Computation times where content and style images are 300x500.

- Patch size of the style swap procedure is an intuitive parameter for changing the degree of abstraction.
- Compared with other optimization approaches, our approach has much fewer local optima.
- Optimization procedure always converges to the same result.
- Allows consistent frame-by-frame performance on videos.

Computation times where content and style images are 300x500.

<table>
<thead>
<tr>
<th>Method</th>
<th>N. Iters</th>
<th>Time/Iter. (s)</th>
<th>Total (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gatys et al. [10]</td>
<td>500</td>
<td>0.1004</td>
<td>50.20</td>
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<tr>
<td>Li and Wand [19]</td>
<td>200</td>
<td>0.6293</td>
<td>125.86</td>
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<tr>
<td>Style Swap (Optim)</td>
<td>100</td>
<td>0.0466</td>
<td>4.66</td>
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<tr>
<td>Style Swap (InvNet)</td>
<td>1</td>
<td>1.2483</td>
<td>1.25</td>
</tr>
</tbody>
</table>

The main bottleneck of our method is the style image size.
Significant speedup can be achieved if the style image is small.