PHOTO STYLE TRANSFER WITH CONSISTENCY LOSSES

Xu YAO
Gilles PUY
Parick PÉREZ
Style Transfer

Neural Style Transfer


$L_t(x) = \alpha L_c(x, x_c) + \beta L_s(x, x_s)$

- Two images are similar in **content** if their high-level features as extracted by a trained classifier are close in Euclidian distance.
- Two images are similar in **style** if the difference between the features’ **Gram matrices** has a small Frobenius norm.
Photo Style Transfer


- Neural Style Transfer on photorealistic style transfer tasks.
Related Work

By adding a regularization term (matting Laplacian) to the objective function of neural style transfer, this method achieves photorealistic style transfer.

Objective: $L_t(x) = \alpha L_c(x, x_c) + \beta L_s(x, x_s) + \lambda L_m(x), L_m(x) = \text{Tr}(x^T L(x_c)x)$
Related Work

Y. Li et al., « A Closed-form Solution to Photorealistic Image Stylization », ECCV 2018

- Fast photorealistic stylization method.
- The algorithm consists of two mappings $\mathcal{F}_1$ and $\mathcal{F}_2$.
  - $\mathcal{F}_1$ maps $x_c$ to an intermediate result in the style of $x_s$.
  - $\mathcal{F}_2$ removes the artifacts and produces a photorealistic stylized result.
Our Approach
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• With no other dataset than **two input photos**️, train CNNs to transfer their styles between each other.
• The output needs to preserve the structure of the content photo, imitate the style of the reference photo, meanwhile, looks like a real photo.
Objective

- **Style Loss**
  - The two networks (→ s, → c) transfer the styles of $x_s$ and $x_c$ respectively.
Objective

- **Content Loss**
  - **Cycle Consistency Loss**
    - If we apply the two networks \((\rightarrow s, \rightarrow c)\) consecutively on \(x_c\), we should get \(x_c\) itself (and vice-versa).

- **Self Consistency Loss**
  - If we transfer the style of one photo to itself, we should get the original photo.

J. Zhu et al., « Unpaired image-to-image translation using cycle-consistent adversarial networks », ICCV 2017
Network Architecture

- Each network transfers one style (for photos having several styles, we train one network for each style).
- During the training, the two networks share the same convolution layers but have different normalization layers which encode different styles.

*V. Dumoulin et al., « A Learned Representation For Artistic Style », ICLR 2017*
Results

F. Luan et al., « Deep Photo Style Transfer », CVPR 2017
Y. Li et al., « A Closed-form Solution to Photorealistic Image Stylization », ECCV 2018
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Two extra advantages of our method

• Generalization to unseen images
• Retraining for new styles
Generalization to unseen images

Even though trained on merely two images, our network can stylize images not viewed at training time.
Retraining for new styles

It is enough to retrain the normalization parameters to adapt our networks to a new style, even though the convolutional layers are pre-trained using only two images.
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Failure Case

Style

Content
Conclusion

- **Our approach**
  - Using only two input photos, we train a pair of deep convolution networks with consistency losses, each of which transfers the style of one photo to the other.
  - Photorealism is achieved thanks to the consistency losses.

- **Two extra advantages**
  - Even though trained on merely two images, our network can stylize images not viewed at training time.
  - To adapt the network for a new style, we only need to retrain a small subset of the parameters.

- **Future work**
  - Reduce the artefacts at the boundary of different semantic regions and reduce the overexposure that sometimes appears in small regions of the results.
  - Adapt the method for arbitrary style transfer.