Deep Photo Style Transfer

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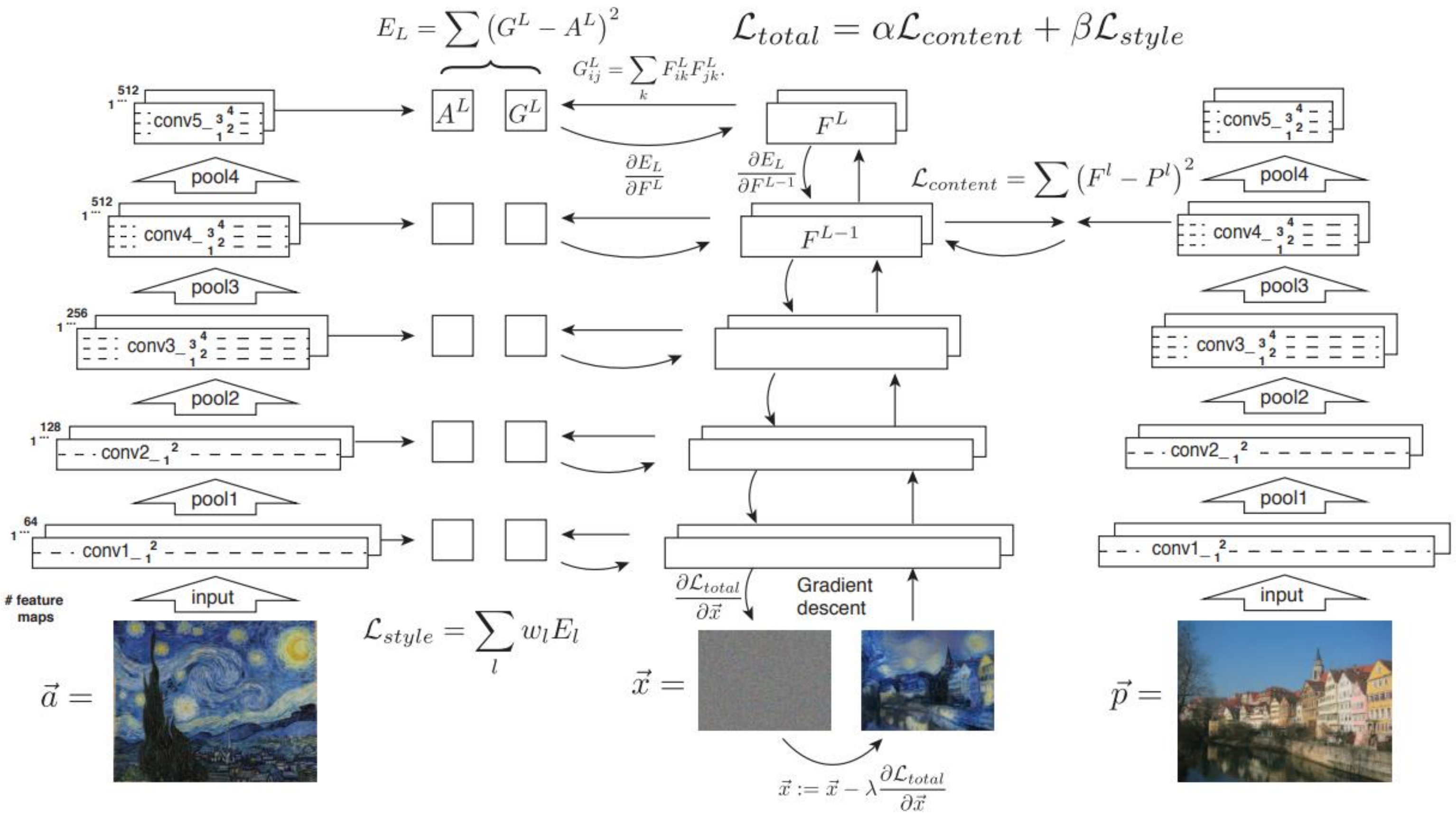
01 Background



$$\mathcal{L}_{\text{total}} = \sum_{\ell=1}^{L} \alpha_\ell \mathcal{L}_c^\ell + \Gamma \sum_{\ell=1}^{L} \beta_\ell \mathcal{L}_s^\ell$$

$$\text{with: } \mathcal{L}_c^\ell = \frac{1}{2N_\ell D_\ell} \sum_{ij} (F_\ell[O] - F_\ell[I])_{ij}^2$$

$$\mathcal{L}_s^\ell = \frac{1}{2N_\ell^2} \sum_{ij} (G_\ell[O] - G_\ell[S])_{ij}^2$$

Average pooling over
19-layer VGG
ReLU

02 Abstract

03-1 Challenge

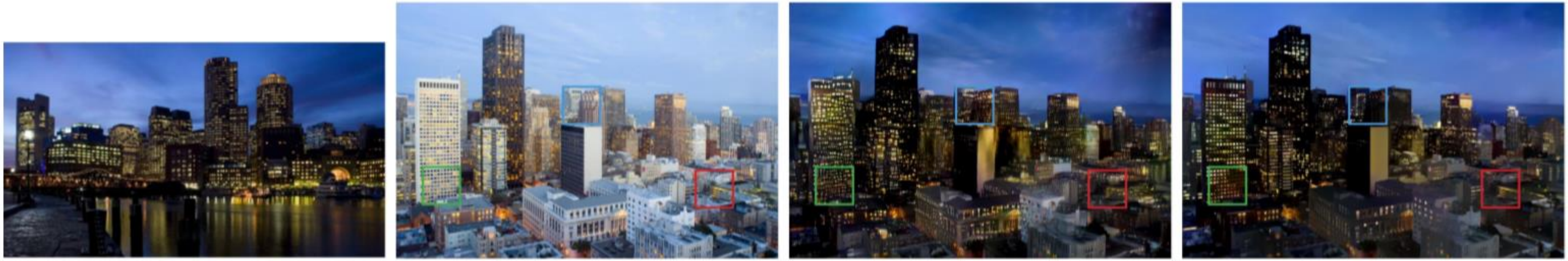
No geom… torts

Minimize… nsfer

03-2 Contribution

1. Structure preservation

2. Semantic accuracy & transfer faithfulness



Photorealism Regularization

$$\mathcal{L}_m = \sum_{c=1}^{3} V_c[$$

$$\mathcal{L}_{\text{total}} = \sum_{l=1}^{L} \alpha_\ell$$

Affine Transformation

Linear transformation that preservers dot, line, plane

Matting Laplacian → Locally affine in color space

04 Methodology

Augmented Style Loss With Semantic Segmentation

$$\mathcal{L}_{s+}^{\ell} = \sum_{c=1}^{C} \frac{1}{2N_{\ell,c}^2} \sum_{ij} (G_{\ell,c}[O] - G_{\ell,c}[S])_{ij}^2$$

$$F_{\ell,c}[O] = F_{\ell}[O] M_{\ell,c}[I] \quad F_{\ell,c}[S] = F_{\ell}[S] M_{\ell,c}[S]$$

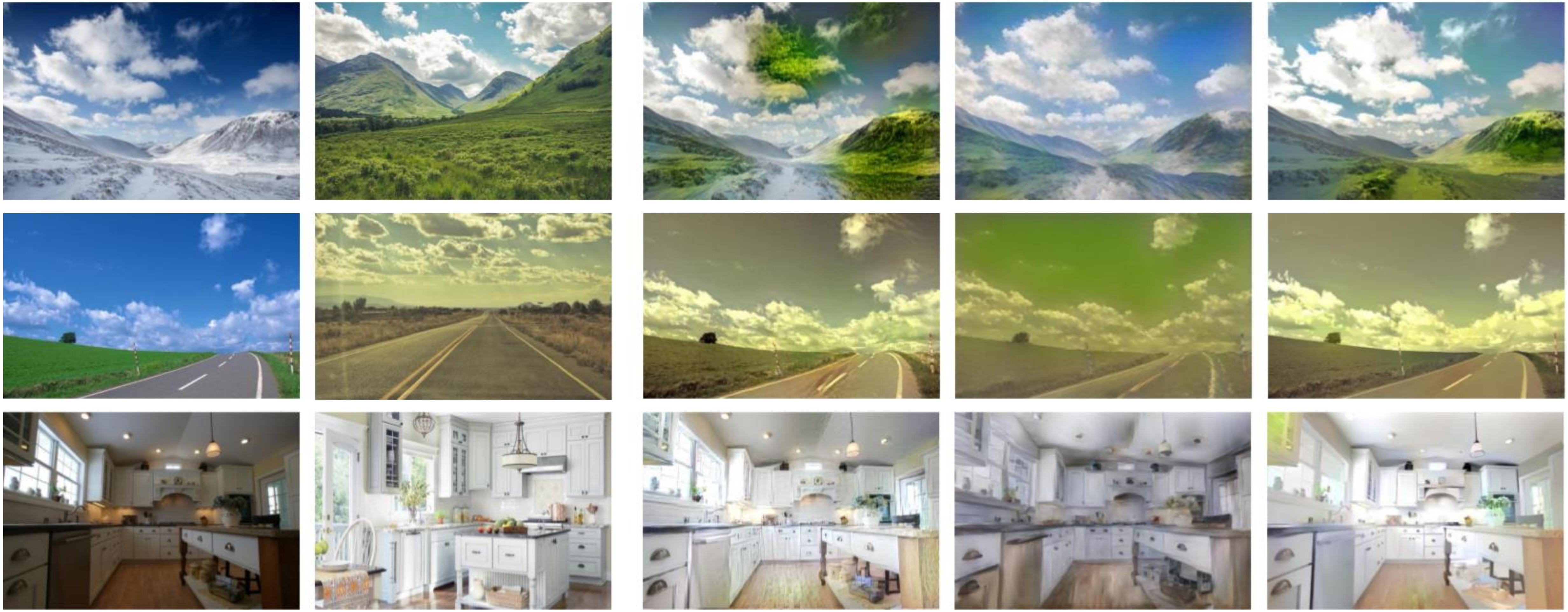
Methodology

Augmented Style Loss With Semantic Segmentation

$$\mathcal{L}_{\text{total}} = \sum_{l=1}^{L} \alpha_\ell \mathcal{L}_c^\ell + \Gamma \sum_{\ell=1}^{L} \beta_\ell \mathcal{L}_{s+}^\ell + \lambda \mathcal{L}_m$$

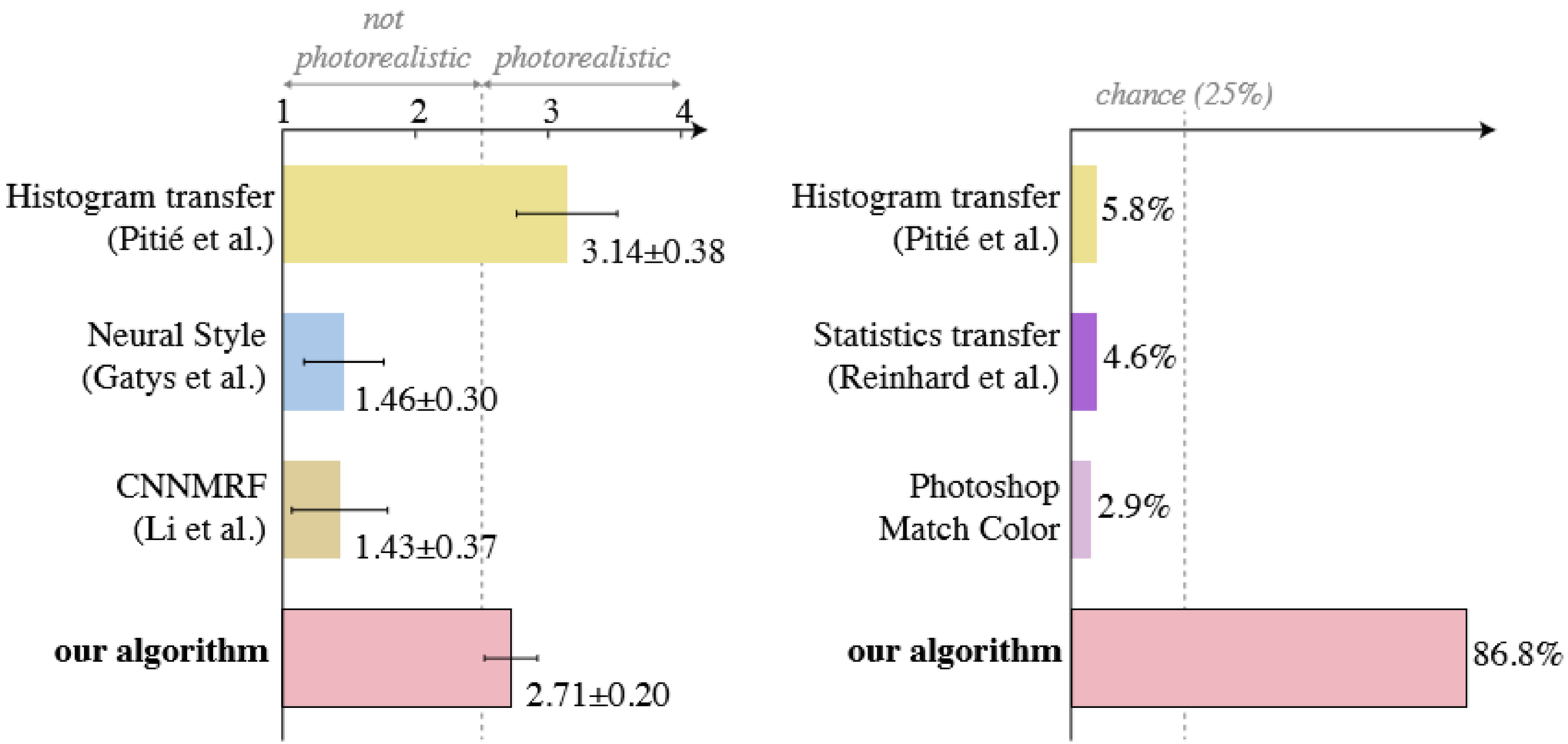
(a) Input and Style (b) $\lambda = 1$ (c) $\lambda = 10^2$ (d) $\lambda = 10^4$, our result (e) $\lambda = 10^6$ (f) $\lambda = 10^8$

05 Result & Comparison



(a) Input image (b) Reference style image (c) Neural Style (d) CNNMRF (e) Our result

05 Result & Comparison



(a) Photorealism scores

(b) Style faithfulness preference

06 Conclusion

We introduce a deep-learning approach that faithfully transfers style from a reference image for a wide variety of image content. We use the Matting Laplacian to constrain the transformation from the input to the output to be locally affine in colorspace. Semantic segmentation further drives more meaningful style transfer yielding satisfying photorealistic results in a broad variety of scenarios, including transfer of the time of day, weather, season, and artistic edits.

Q&A