

MetaStyle: Three-Way Trade-Off Among Speed, Flexibility and Quality in Neural Style Transfer



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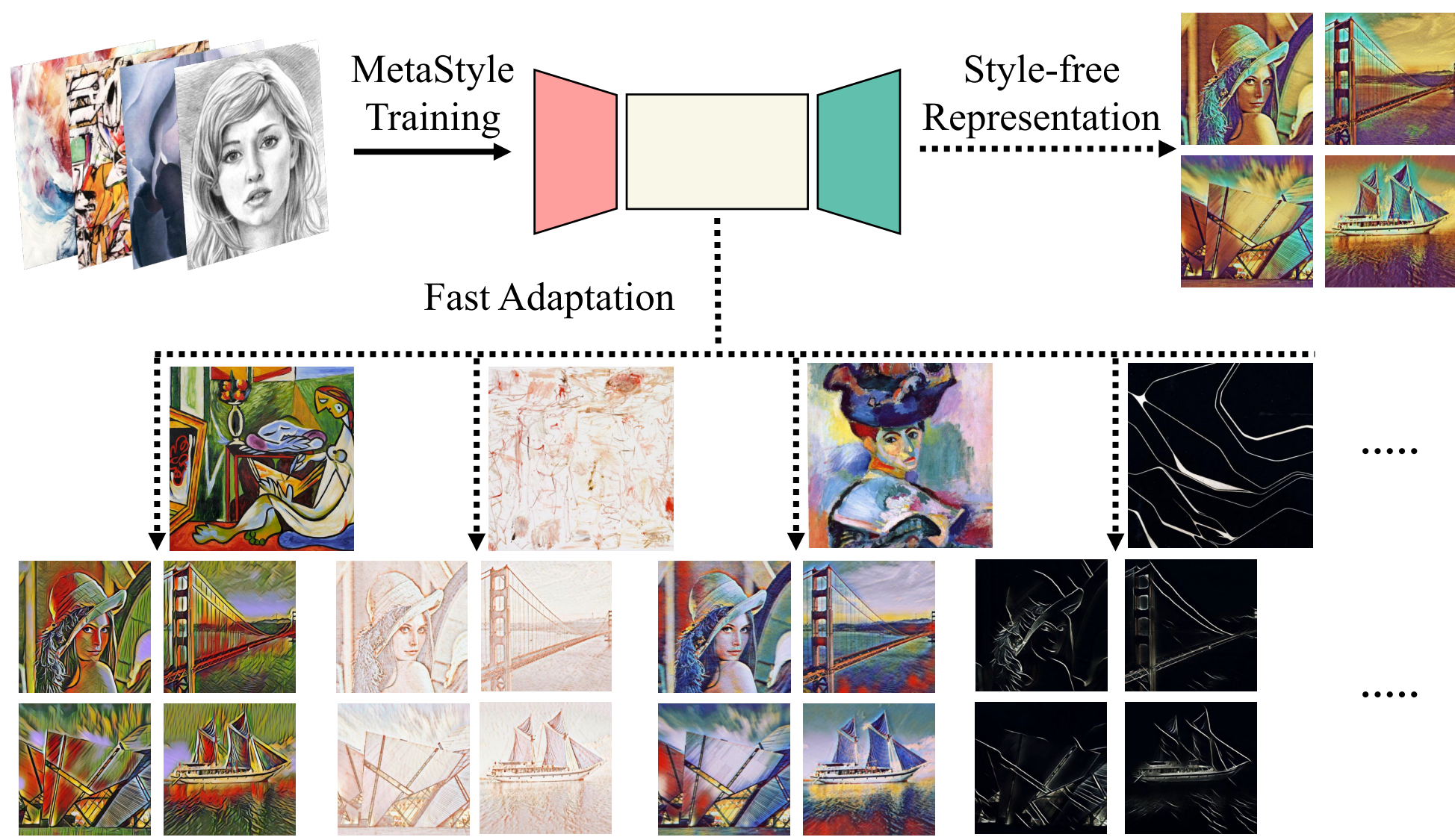
Motivation

Method	Speed	Flexibility	Quality	Drawback
Optimization-based	Slow	Any	High	Run for each content-style pair
Fast approximation	Fast	Single	High	Train long for each new style
Feature matching	Fast	Any/Several	Compromised	Limited set of styles, low quality

Can we find a style transfer algorithm that could quickly adapt to any style, while the adapted model maintains high efficiency and good image quality?

MetaStyle

Framework



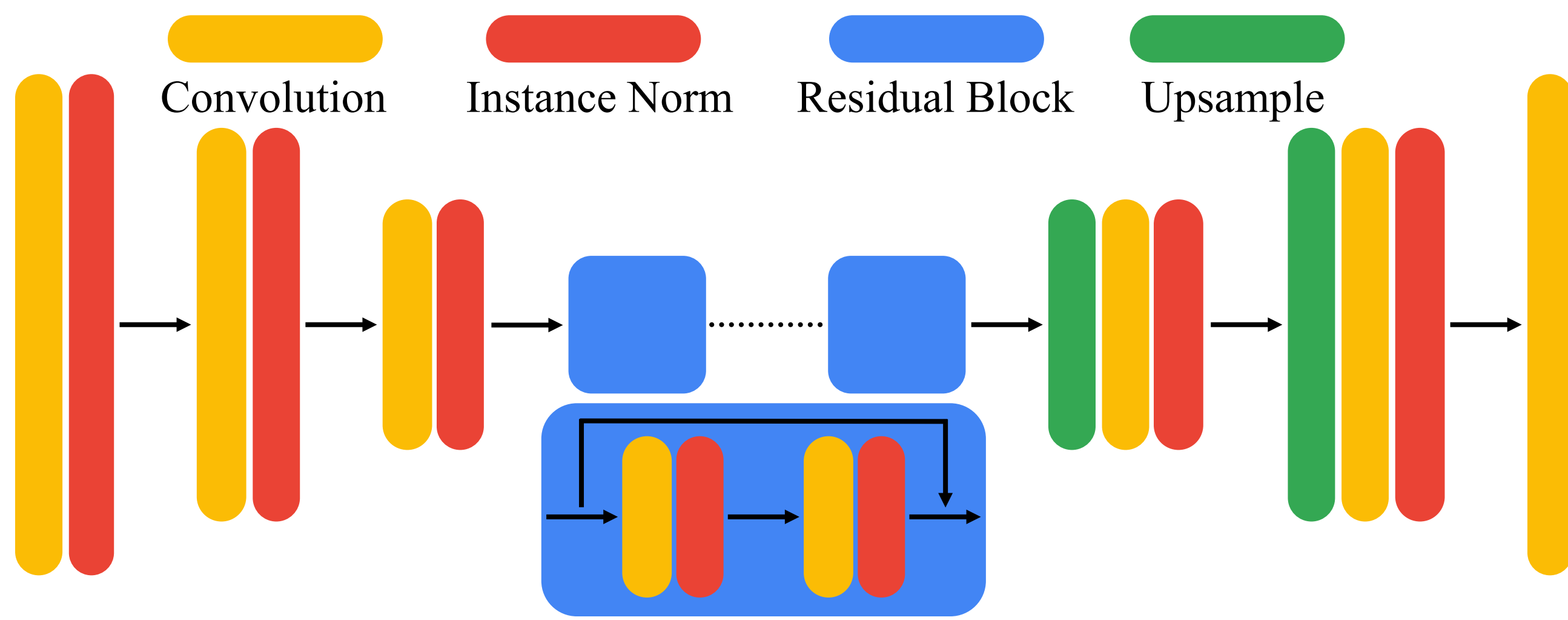
Training

$$\begin{aligned} &\underset{\theta}{\text{minimize}} && \mathbb{E}_{c,s}[\ell(I_c, I_s, M(I_c; w_{s,T}))] \\ &\text{subject to} && w_{s,0} = \theta \\ &&& w_{s,t} = w_{s,t-1} - \delta \nabla \mathbb{E}_c[\ell(I_c, I_s, M(I_c; w_{s,t-1}))] \end{aligned}$$

Adaptation

$$\underset{w}{\text{minimize}} \quad \mathbb{E}_c[\ell(I_c, I_s, M(I_c; w))]$$

Network



Algorithm

Algorithm 1: MetaStyle

Input : content training dataset \mathcal{D}_{tr} , content validation dataset \mathcal{D}_{val} , style dataset \mathcal{D}_{style} , inner learning rate δ , outer learning rate η , number of inner updates T

Output: trained parameters θ

randomly initialize θ

while not done **do**

 initialize outer loss $E \leftarrow 0$

 sample a batch of styles from \mathcal{D}_{style}

for each style I_s **do**

$w_s \leftarrow \theta$

for $i \leftarrow 1$ to T **do**

 sample a batch \mathcal{B}_{tr} from \mathcal{D}_{tr}

 compute inner loss L_θ using I_s and \mathcal{B}_{tr}

$w_s \leftarrow w_s - \delta \nabla L_\theta$

end

 sample a batch \mathcal{B}_{val} from \mathcal{D}_{val}

 increment E by loss from I_s and \mathcal{B}_{val}

end

$\theta \leftarrow \theta - \eta \nabla E$

end

Quantitative Results

Method	Param	256 (s)	512 (s)	# Styles
Gatys <i>et al.</i>	N/A	7.7428	27.0517	∞
Johnson <i>et al.</i>	1.68M	0.0044	0.0146	1
Li <i>et al.</i>	34.23M	0.6887	1.2335	∞
Huang <i>et al.</i>	7.01M	0.0165	0.0320	∞
Shen <i>et al.</i>	219.32M	0.0045	0.0147	∞
Sheng <i>et al.</i>	147.22M	0.5089	0.6088	∞
Chen <i>et al.</i>	1.48M	0.2679	1.0890	∞
Ours	1.68M	0.0047	0.0145	∞^*

Qualitative Results

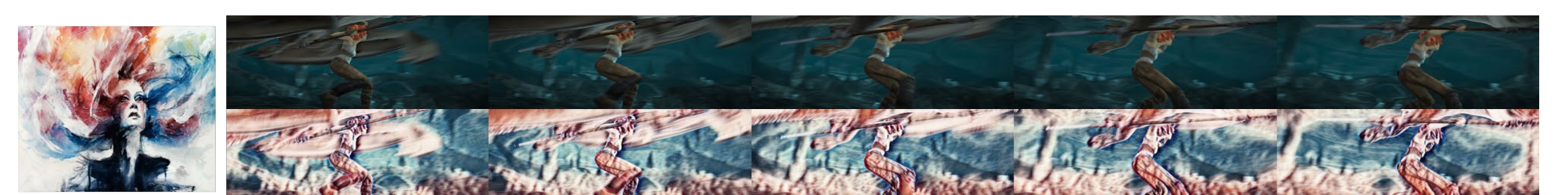
Comparison with Existing Methods



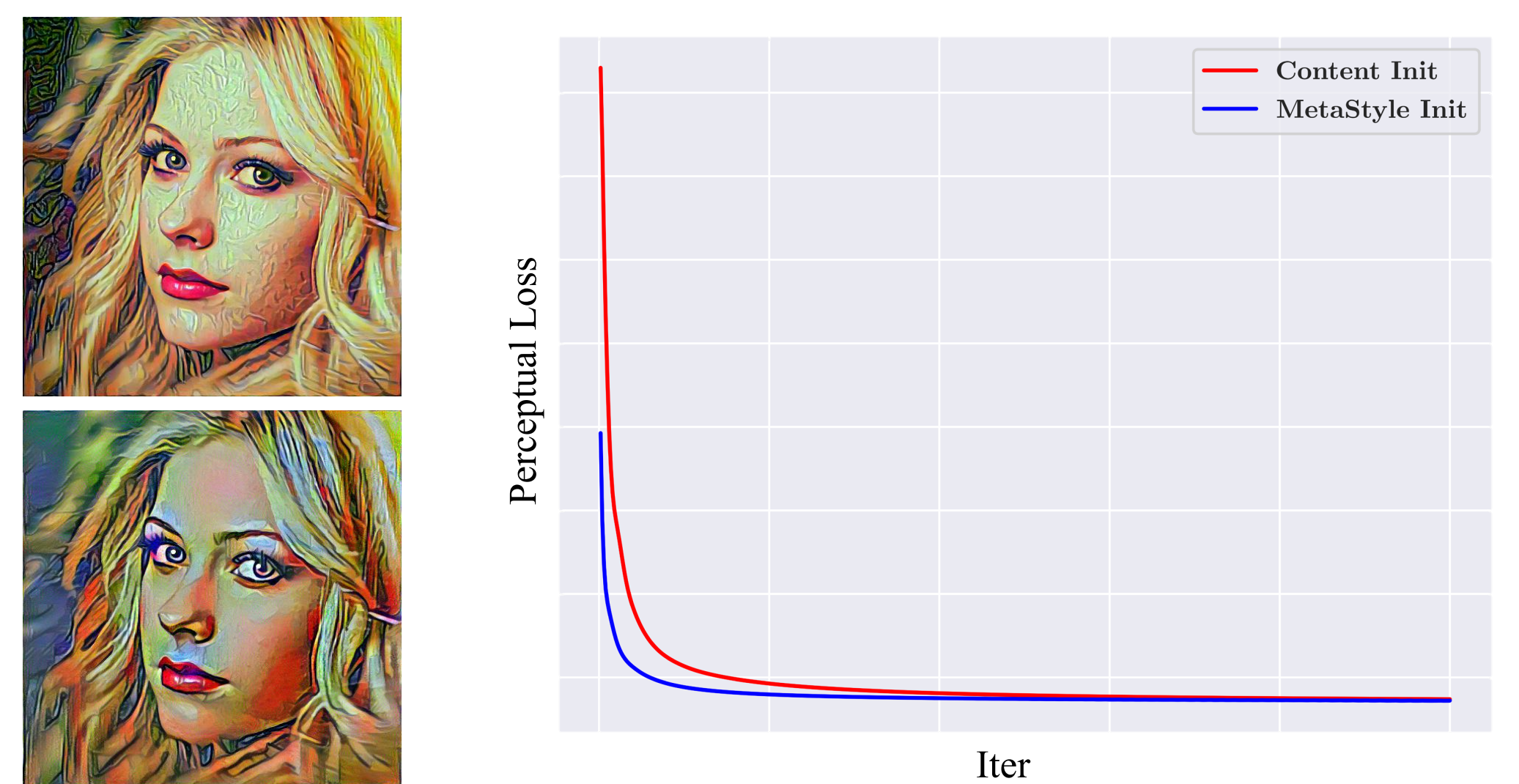
Style Interpolation



Video Style Transfer



Comparison to Gatys et al. with MetaStyle Init



Comparison to Johnson et al. with MetaStyle

