

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



Chi Zhang, Yixin Zhu, Song-Chun Zhu  
International Center for AI and Robot Autonomy  
{chizhang, yzhu, sczhu}@cara.ai



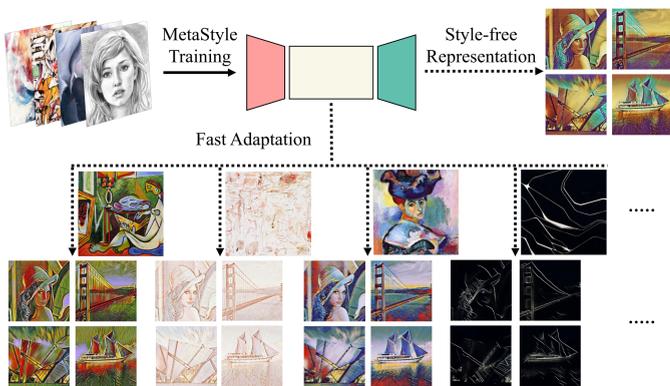
## Motivation

| 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



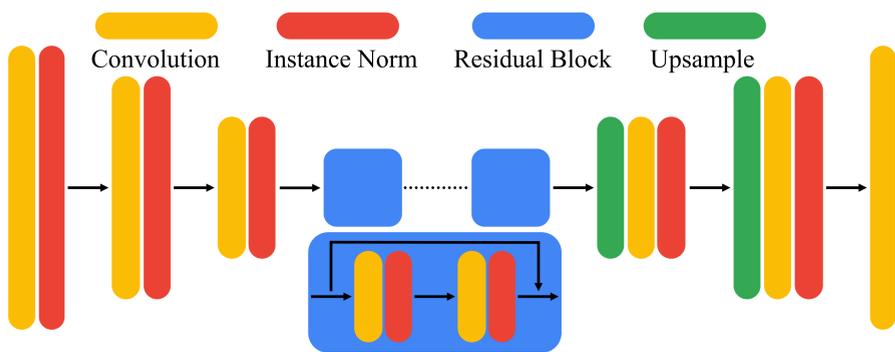
### Training

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

### Adaptation

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

## 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  $\delta$ , outer learning rate  $\eta$ , number of inner updates  $T$

**Output**: trained parameters  $\theta$

randomly initialize  $\theta$

**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  $L_\theta$  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**

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

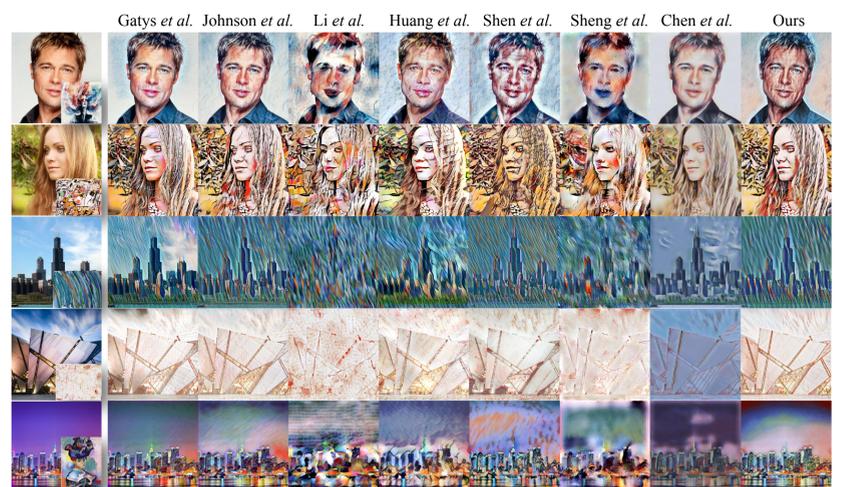
**end**

## Quantitative Results

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

## Qualitative Results

### Comparison with Existing Methods



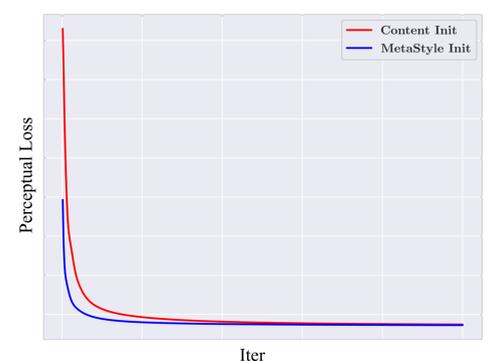
### Style Interpolation



### Video Style Transfer



### Comparison to Gatys *et al.* with MetaStyle Init



### Comparison to Johnson *et al.* with MetaStyle

