DRB-GAN: A Dynamic ResBlock Generative Adversarial Network for Artistic Style Transfer

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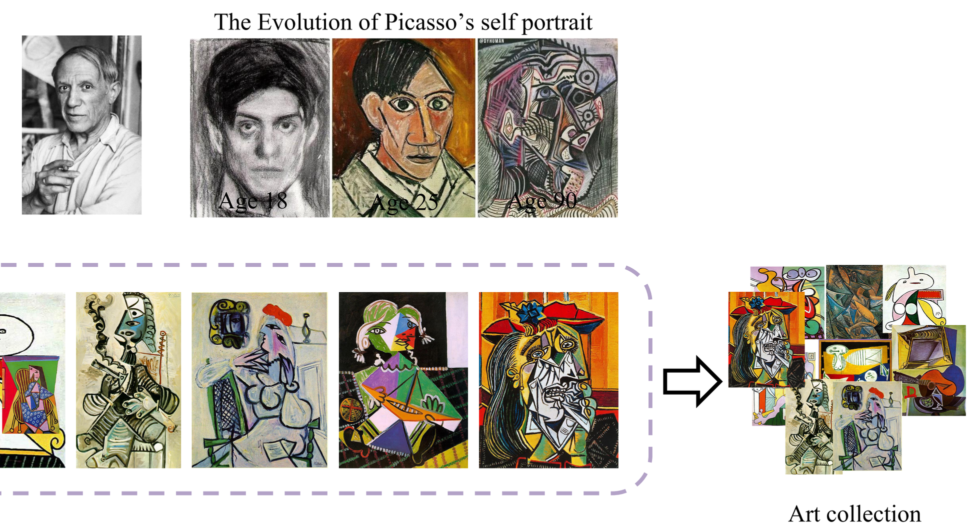
Introduction

Artistic style transfer

- Synthesize an image sharing structure similarity of the content image and reflecting the artistic style.



- Style is not only in one individual style image but also a reflection of an art collection.
- Arbitrary style transfer cannot benefit from other style images sharing similar style.
- Collection style transfer only recognize and transfer the domain dominant style clues and thus lack the flexibility of exploring style manifold.

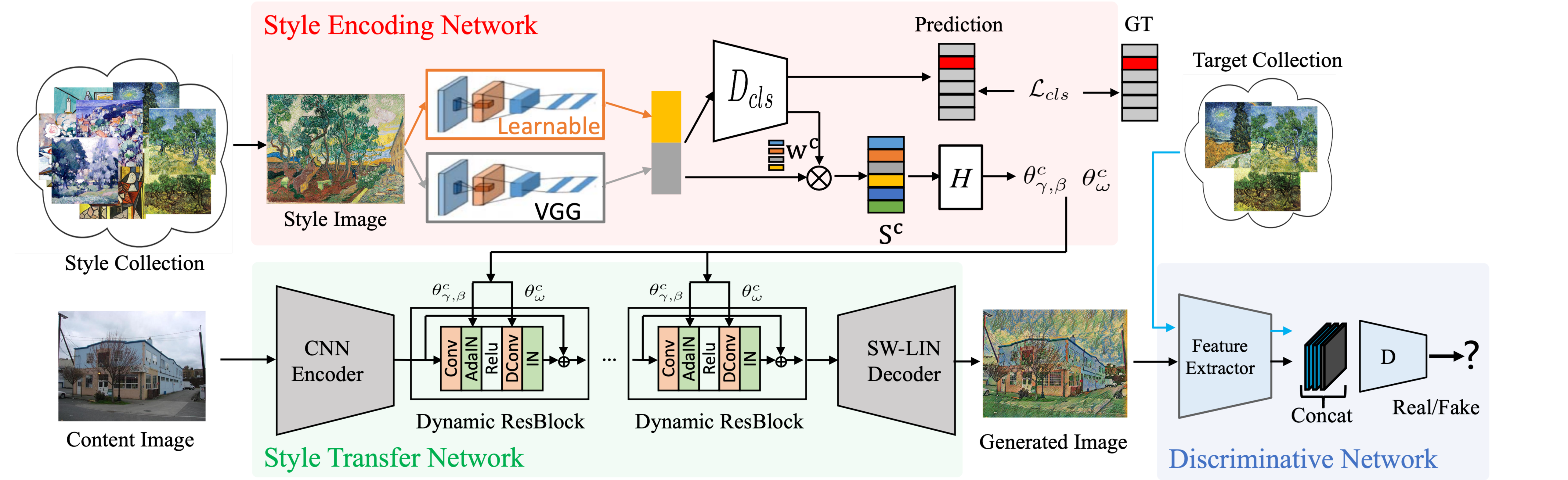
Contribution

- A unified Model that handle arbitrary style transfer and collection style transfer.
- "style codes" is modeled as the dynamic parameters within Dynamic ResBlocks.
- Style consistency & Content structural similarity.

Datasets & Metrics

- Dataset: Place365 dataset and Wikiart dataset.
- Metrics: Deception score, Human study and Memory consumption.
- Project: https://github.com/xuwenju123/DRB-GAN.

DRB-GAN



- Style encoding network
  - Learnable CNN & Pretrained VGG
  - Style recalibration
- "style code" in dynamic ResBlocks:

$$\{\theta^c_{\omega}, \theta^c_{\gamma,\beta}\} = \{H_{\omega}(s^c), H_{\gamma,\beta}(s^c)\}$$

- "collection style code" as a weighted mean of the "style codes":

$$\{\bar{\theta}^c_{\omega},\ \bar{\theta}^c_{\gamma,\beta}\} = \{\frac{1}{K}\sum_{k=0}^{K}\pi_k\theta^c_{\omega_k},\ \frac{1}{K}\sum_{k=0}^{K}\pi_k\theta^c_{\gamma_k,\beta_k}|c \sim N\}$$

- Style transfer network
  - Dynamic ResBlock
  - SW-LIN Decoder

$$\text{SW-LIN}(\gamma,\beta,\rho) = \gamma(\rho\phi^c_{sw} + (1-\rho)\phi^l_{sw}) + \beta$$

$$\phi_{sw} = \frac{\mathbf{h} - E_{x_i \in sw}[\mathbf{h}(x_i)]}{\sqrt{Var_{x_i \in sw}[\mathbf{h}(x_i)]}}$$

- Preserve local feature.
- Remove artifacts.

- Discriminative network
  - Discriminate on image and target style collection

$$\mathcal{L}_{adv} = E_{y^c, y^c_i \sim Y, c \sim N}[-\log D(y^c, \{y^c_i\}^M_{i=0})] + E_{\tilde{x}^c \sim G(x), y^c_j \sim Y, c \sim N}[-\log(1 - D(\tilde{x}^c, \{y^c_j\}^M_{j=0}))]$$

- Better style consistency

Comparison Experiments with State-of-the-art Approaches

- Arbitrary Style Transfer

Method	Time (sec)	GPU memory (MiB)	Model	Deception rate	Human studies Content score	Human studies Style score
Wikiart test				0.626	-	-
Gatys *et al.*	200	3887	PSPM	0.251	67.1%	0.127
AdaIN	0.16	8872	ASPM	0.061	43.6%	0.019
WCT	5.22	10720	ASPM	0.023	39.2%	0.013
PatchBased	8.70	4159	ASPM	0.063	53.4%	0.043
Johnson	0.06	671	ASPM	0.080	38.5%	0.021
CycleGAN	0.07	1391	PDPM	0.130	43.2%	0.012
AST	0.07	1043	PDPM	0.450	63.9%	0.312
DRB-GAN	0.08	1324	MDPM	**0.573**	**72.2%**	**0.453**

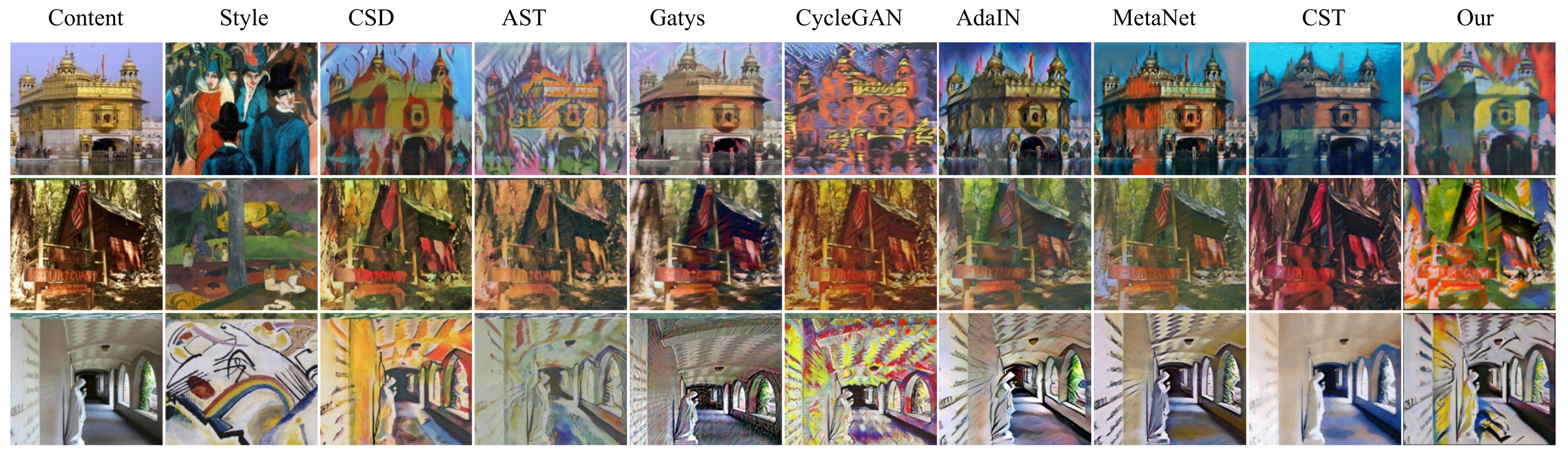
- Collection Style Transfer

Table 2. Quantitative comparison of different methods. SD stands for style distance metric; DS represents deception score.

Setting	Arbitrary Style (SD↓)	Collection style (DS↑) K=2	5	10	20
AdaIN	263.4	0.066	0.045	0.013	0.011
MetaNet	271.8	0.032	0.026	0.023	0.020
DRB-GAN	**241.2**	**0.576**	**0.580**	**0.581**	**0.583**

Visualization and Robustness Analysis

Visualization Comparison with State-of-the-art Approaches



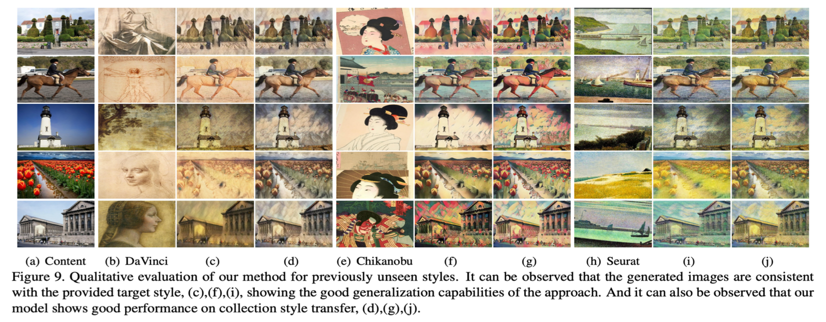
Visualization on Ablation Study

- Collection discriminator

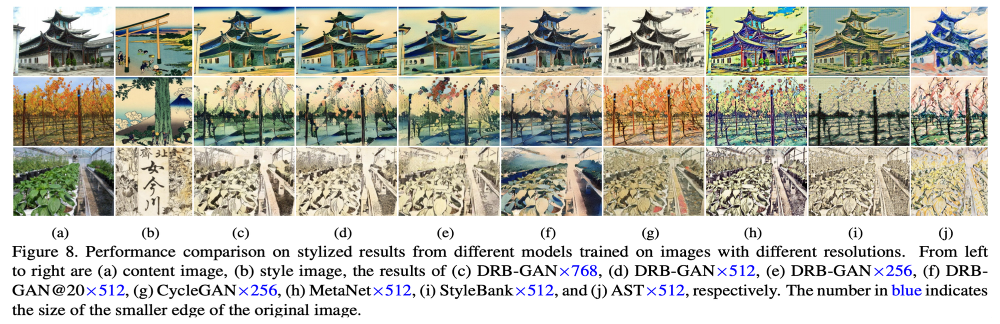
- SW-LIN Decoder

Robustness Analysis

- Unseen style

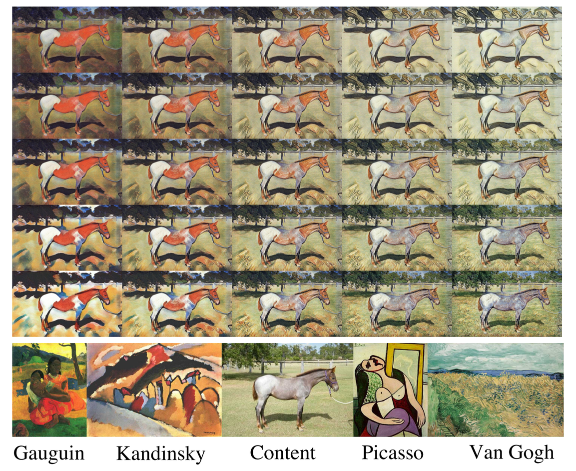


- Different resolutions



- HD resolution

- Interpolation



Key References

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