Interactive Style Space of Deep Features and Style Innovation

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Main research problem statement

- **Motivation:** Single style transfer is very popular recently. However, few works systematically discussed the interpolated styles generated by multi-style transfer.
- **Tasks:** We generalize the style transfer problem as a series of solvable objective optimization problems. Then we construct a style space (Interactive Style Space, ISS) which enables systematic style innovation using interpolation of known styles.
- **Key idea:** Utilize the low-level features and high-level features of paintings. Perform style interpolation to explore unknown styles in a style space based on Wasserstein distance.

Image Features Introduction

- Low-level features: such as color, shading, stroke pattern and many more
- Middle-level features: such as geometry, perspective, line style and many more
- High-level features: such as decomposition, objects presence and several others

Content : the objects in the painting…

Style: color, shading, stroke pattern…

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Style Transfer Problem Generalization

- **Painting Depiction (f)**

content (c): the objects in the painting…

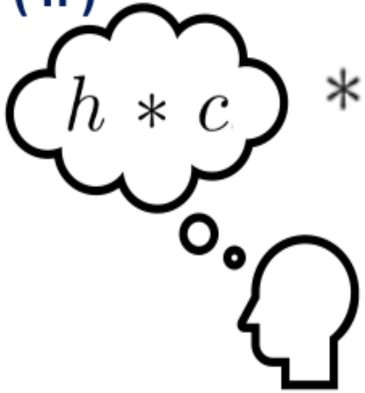
presentational form [style] (s): color, shading, stroke pattern…

$$f = s \circ c$$

Painting depiction (f)

$\bigcirc$: Style Transfer operation

- **Human Perception (h)**



$*$: The operation of human perception

Human perception (h) towards the content (c)

- **Expanded Generalization**

Algorithm (t): recognize the style (s)

$$t \star f$$

$\star$: Machine's recognition operation

- For a meaningful artwork, the human perceived depiction h $*$ f should be as close as possible to the human perceived content h $*$ c:

$$\min_{f} \|h * f - h * c\|_a = \min_{f} \|h * (s \circ c) - h * c\|_a \qquad (1)$$

- For the specific form of paintings with a style, the form recognized from the depiction t $\star$ f should be as close as possible to the style s:

$$\min_{f} \|t \star f - s\|_b = \min_{f} \|t \star (s \circ c) - s\|_b \qquad (2)$$

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Style Transfer Problem Generalization

Then, we can formulate the artistic painting depiction as a multiple objective optimization problem (Image Stylization problem):

$$f^{\star} = \underset{f}{argmin} \left\{ \|h * f - h * c\|_a , \|t \star f - s\|_b \right\} = \underset{f}{argmin} \left\{ \|h' * (s \circ c) - h * c\|_a , \|t \star (s \circ c) - s\|_b \right\} \quad (3)$$

Add the positive constant α, the above problem can be implemented as a single objective optimization problem:

$$f^{\star} = \underset{f}{argmin} \left\{ \|h * f - h * c\|_a + \alpha \|t \star f - s\|_b \right\} = \underset{f}{argmin} \left\{ \|h * (s \circ c) - h * c\|_a + \alpha \|t \star (s \circ c) - s\|_b \right\} \quad (4)$$

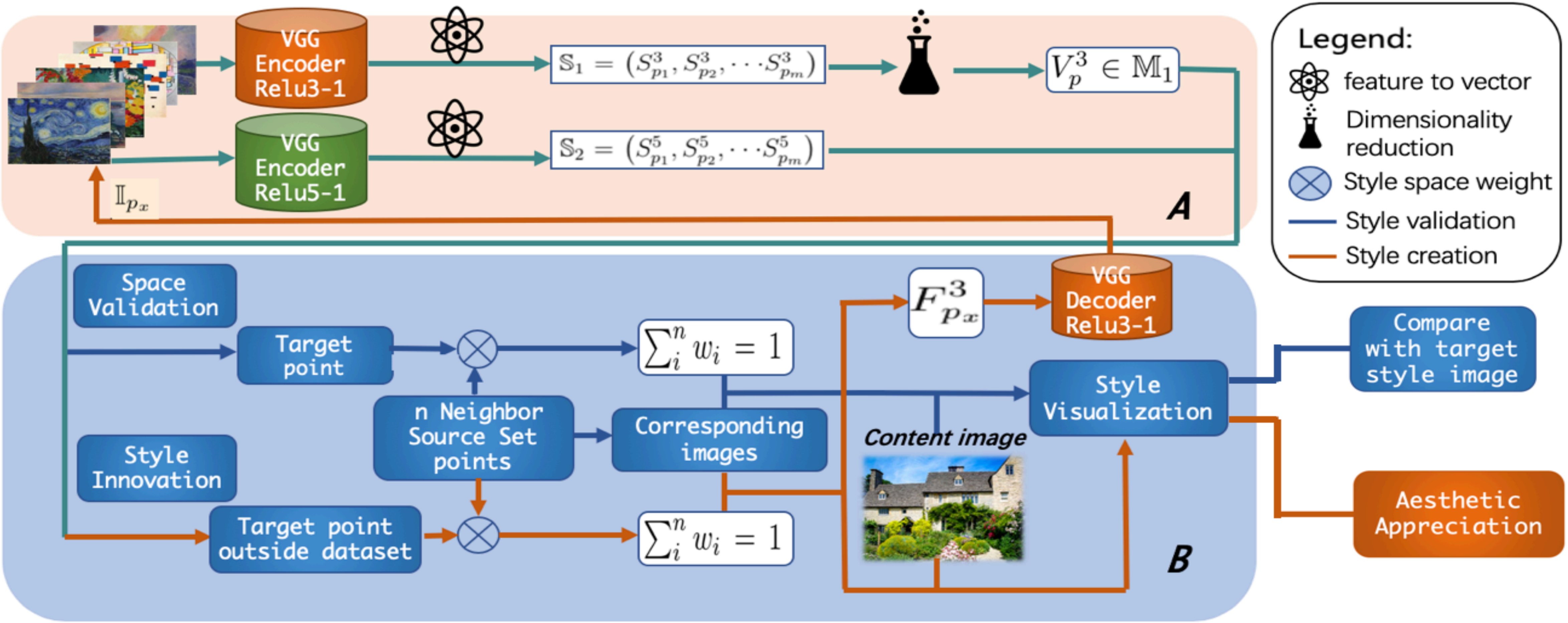
- **Style Innovation problem:**

To compare the similarity of styles (s1 and s2) between two images (f1 and f2) with contents (c1 and c2):

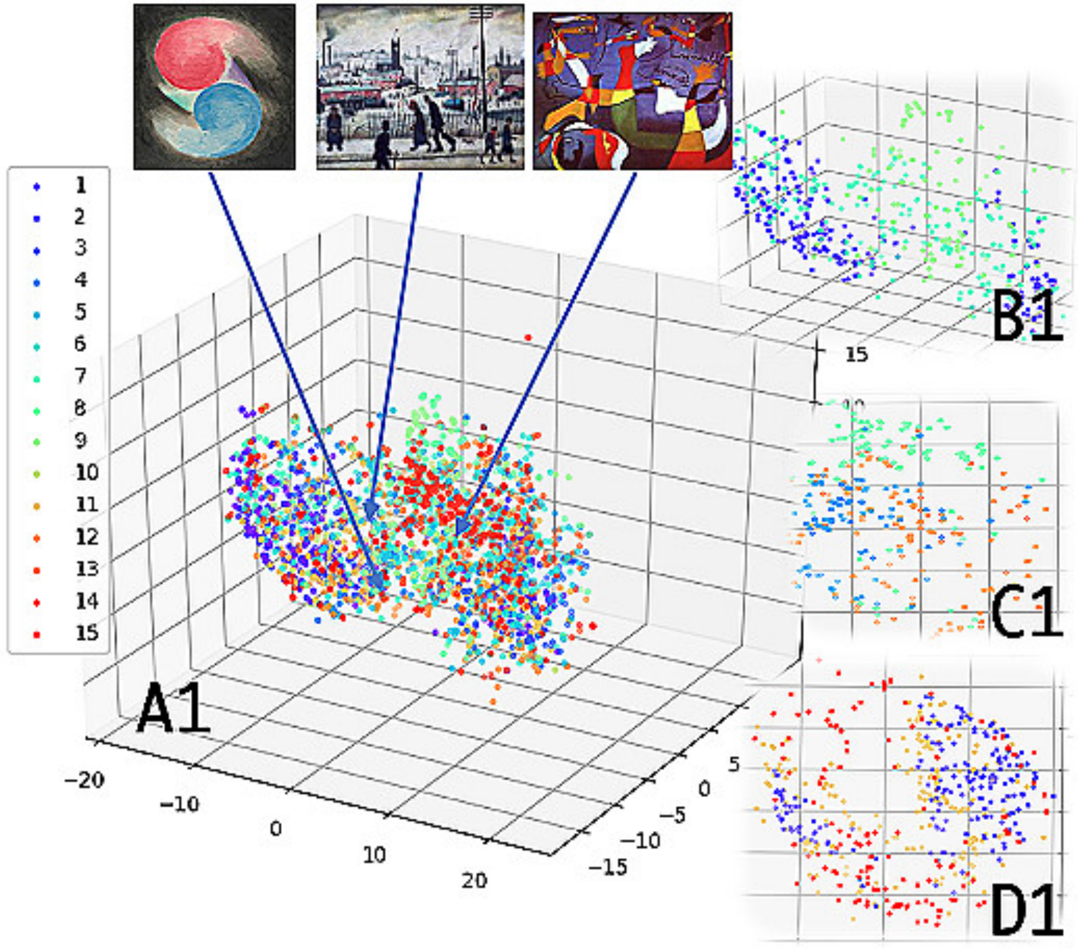
$$\|t \star f_1 - t \star f_2\|_b = \|t \star (s_1 \circ c_1) - t \star (s_2 \circ c_2)\|_b \quad (5)$$

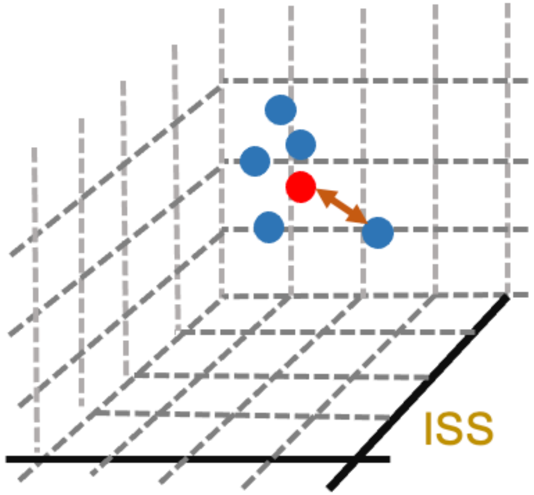
$\|*\|_b$ measures the similarity/difference between two styles. For innovation problem, the difference between s1 and s2 should as large as possible.

The Framework of Our Method



Interactive Style Space (ISS) Validation





● Target point (pi)

● N neighbor source points (pn). (in this example, N=5)

Euclidean distance between Target point and Source point

S_N^5 Normalized 5th layer Style Vector

$$V_p^n = \left(x_p^n, y_p^n, z_p^n\right), n = 3 \qquad (6)$$

$$d_{ix} = \alpha Dis\left(V_{p_i}^3, V_{p_x}^3\right) + \beta Dis\left(S_{Np_i}^5, S_{Np_x}^5\right), \ \alpha + \beta = 1 \qquad (7)$$

$$w_i = d_{ix}^{-1} / \left(\sum_i^n d_{ix}^{-1} \cdot (1 - w_c)\right) \qquad (8)$$

- Style visualization: Wasserstein Style Transfer [1]:

$$T^{\mathfrak{W}}_{F_c^n \to F_{p_x}^n}(x) = m_{p_x}^n + \left(\sigma_c^n\right)^{-\frac{1}{2}} \left[\left(\sigma_c^n\right)^{\frac{1}{2}} \left(\sigma_{p_x}^n\right) \left(\sigma_c^n\right)^{\frac{1}{2}}\right] \left(\sigma_c^n\right)^{-\frac{1}{2}} \cdot \left(x - m_c^n\right) \qquad (9)$$

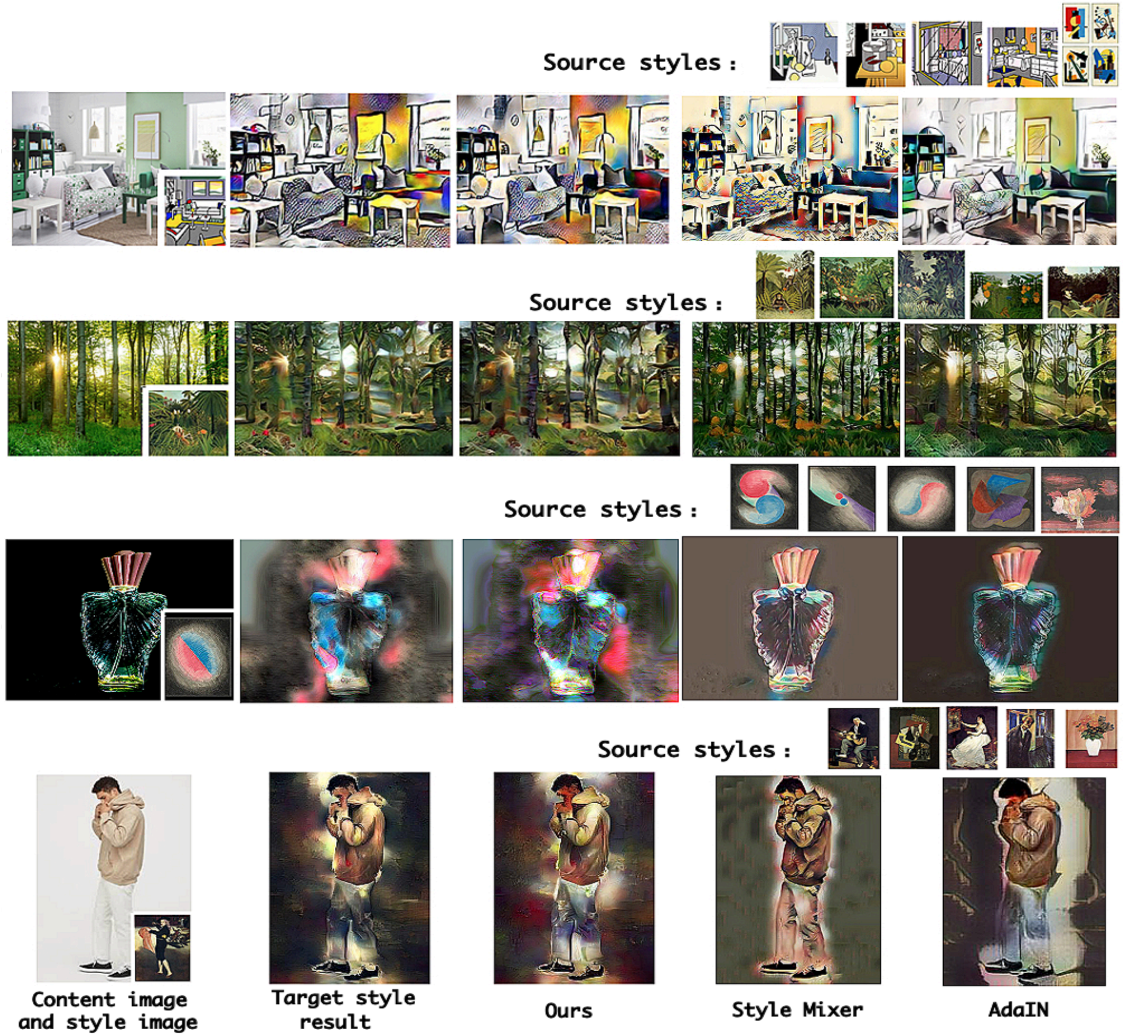
$$I_{p_x}^n = D^n\left(T^{\mathfrak{W}}_{F_c^n \to F_{p_x}^n}\left(E^n\left(I_c\right)\right)\right) \qquad (10)$$

[1] Y. Mroueh, "Wasserstein style transfer," *arXiv preprint arXiv:1905.12828*, 2019.

Quantitative Evaluation and Comparison of Validation Results

Evaluation Quality		Pixel-wise Mse	Wasserstein Distance	Style vector ReLU3-1	Style vector ReLU5-1
Evaluation Examples	Image 1	9.2958	0.0112	0.1484	0.4666
	Image 2	12.0209	0.0145	0.1256	0.5684
	Image 3	10.3374	0.0104	0.1883	0.4888
	Image 4	40.3908	0.2044	0.4748	0.7733
	Image 5	42.5435	0.1725	0.3391	0.7003
	Image 6	43.0349	0.2319	0.7763	0.8544
(α, β)	(0.9,0.1)	1.9675	0.0196	0.0334	0.1656
	(0.7,0.3)	**1.9626**	0.0196	0.0328	0.1674
	(0.5,0.5)	1.9669	0.0196	0.0338	0.1659
	(0.3,0.7)	2.2530	0.0189	0.0325	0.1541
	(0.1,0.9)	2.2148	0.0205	0.0255	0.1329
n	2	3.6548	0.0242	0.0542	0.1684
	4	2.3035	0.0206	0.0394	0.1879
	5	**1.9626**	0.0196	0.0338	0.1674
	6	1.9683	0.0195	0.0299	0.1537
	10	2.3225	0.0217	0.0293	0.1481

Quantitative Evaluation and Comparison of Validation Results



Style Innovation Examples