Name Your Style: An Arbitrary Artist-aware Image Style Transfer

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Abstract—Image style transfer has attracted widespread attention in the past few years. Despite its remarkable results, it requires additional style images available as references, making it less flexible and inconvenient. Using text is the most natural way to describe the style. More importantly, text can describe implicit abstract styles, like styles of specific artists or art movements. In this paper, we propose a text-driven image style transfer (TxST) that leverages advanced image-text encoders to control arbitrary style transfer. We introduce a contrastive training strategy to effectively extract style descriptions from the image-text model (i.e., CLIP), which aligns stylization with the text description. To this end, we also propose a novel and efficient attention module that explores cross-attentions to fuse style and content features. Finally, we achieve an arbitrary artist-aware image style transfer to learn and transfer specific artistic characters such as Picasso, oil painting, or a rough sketch. Extensive experiments demonstrate that our approach outperforms the state-of-the-art methods on both image and textual styles. Moreover, it can mimic the styles of one or many artists to achieve attractive results, thus highlighting a promising direction in image style transfer.

Index Terms—Style transfer, language processing, image processing, multimodality.

1 INTRODUCTION

Image style transfer is a popular topic that aims to apply desired painting style onto an input content image. The transfer model requires the information of “what content” in the input image and “which painting style” to be used. Conventional style transfer methods require a content image accompanied by a style image to provide the content and style information. However, people have specific aesthetic needs. Usually, it is inconvenient to find a proper style image that perfectly matches one’s requirements. Text or language is a natural interface to describe which style is preferred. Instead of using a style image, using text to describe style preference is easier to obtain and more adjustable. Furthermore, achieving perceptually pleasing artist-aware stylization typically requires learning from collections of arts, as one reference image is not representative enough. Figure 1 shows the artist-aware stylization (Van Gogh and El-Greco) on two examples, a sketch and a photo. For each example, we display four stylizations: (1) style-specific optimization (AST [1]), (2,3) text-driven optimization (CLIPstyler [2], and text-aware stylization (Ours, TxST). Note there are two versions of CLIPstyler. CLIPstyler(opti) requires real-time optimization on each content and each text. CLIPstyler(fast) requires real-time optimization on each text. Hence, both CLIPstyler and AST are time-consuming. We observe that AST grasps the style from the artist’s work, but it does not preserve the content. CLIPstyler(slow) fails to learn fine styles and colors. CLIPstyler(opti) also fails to learn the most representative style but instead, it pastes specific patterns, like the face on the wall in Figure 1(b). In contrast, TxST successfully mimics the artists’ style (curvature of Van Gogh, dark twisted lines of El-Greco) while preserving the content cues.

Fig. 1. Artist-aware style transfer. We show two examples of using different methods for style transfer: (a) AST (style-specific), (b) Clipstyler (fast and opti) and (c) our proposed TxST. Example (a) uses a sketch as a content to transfer Van Gogh style. Example (b) uses a photo as a content to transfer El-Greco style. AST fails to preserve the content information and CLIPstyler cannot transfer the correct styles from the text, such as the faces on the wall produced by CLIPstyler (opti) in (b). Instead, TxST successfully mimics the artists’ style (curvature of Van Gogh, dark twisted lines of El-Greco) while preserving the content cues.

In this work, we aim to learn arbitrary artist-aware image style transfer, which transfers the painting styles of

1. Landscape Sketch with a Lake drawn by Markó, Károly (1791–1860)
any artists to the target image using texts and/or images. Previous studies on universal image style transfer [1], [3], [4] limit their applications to using reference images as style indicator that are less creative or flexible. As shown in Figure 1, AST [1], one of the state-of-the-art artist style transfer methods, learns a dedicated model for one specific style, which usually overemphasizes the styles from artists that the output loses content information. On the contrary, TxST can use the text Van Gogh to mimic the distinctive painting features (e.g., curvature) onto the content image. Text-driven style transfer has been studied by [5] and [2], and shown some promising results using a simple text prompt. However, they either require costly data labelling and collection, or require online optimization for each content and each style (as CLIPstyler(fast) and CLIPstyler(opti) in Figure 1). Our proposed TxST overcomes these two problems and achieves much better and more efficient stylization.

Previous works, like CLIPstyler, have been devoted to implementing text-driven style transfer. Our proposed TxST explicitly adopts this idea to achieve artist-aware style transfer. That is, we try to find the hidden space where the global distance of different artworks (different artists) can be maximized, while the same artworks (same artists) can be minimized. The process of our proposed TxST is shown in Figure 2. We randomly sample two style images ($I_i^1$ and $I_i^2$) from two artists, then we minimize the distance between the target texts and generated images ($\Delta T_1$ and $\Delta T_2$), while maximizing the distance between two generated images $\Delta D$. It can resonate with the classic Fisher Linear Discriminant [6] to distribute features into groups. Specifically, given artists’ names known as a prior, we project features from different artworks onto the CLIP space for classification.

In this work, we empirically analyze the co-linearity between artists and paintings on the CLIP space to demonstrate the reasonableness and effectiveness of text-driven style transfer. Our experiments on both image- and text-driven style transfer show that the proposed approach outperforms other state-of-the-art quantitatively and qualitatively. The key contributions of our proposed artist-aware image style transfer can be summarized as follows.

- To achieve text-driven image style transfer, we propose to embed the task-agnostic image-text model, i.e., CLIP, into our network. This enables our network to obtain style preference from images or text descriptions, making the image style transfer more interactive. (Sections 3.4.1)

- We propose a polynomial attention module to estimate polynomial cross-correlations between content and style features. To restore style preference in the spatial domain, we propose a novel positional mapper that expands the 1-D CLIP code into 2-D space for position awareness. Based on the restored style preference and cross-correlations, the content feature is then projected with target style preference, which significantly improves the effectiveness of the style transfer (Section 4.2).

- We propose to use Constrastive training strategy (Sections 3, 4.2) to learn art collection awareness, equivalent to a self-supervised classification. This studies the inter-class similarity of different artists without explicit label guidance and data collection.

- We conduct extensive experiments on both general and artist-aware style transfer using both style images and texts. We show that our proposed TxST outperforms the state of the art using both quantitative and qualitative evaluations. To demonstrate the generability and applicability of TxST to other tasks, we also conduct studies on multiple style transfer and high-resolution style transfer.

## 2 Related Work

Here, we introduce three related topics: arbitrary and domain-aware style transfer and text-driven image editing. **Arbitrary style transfer.** It can be categorized into two groups: (1) style-aware optimization [7], [8], [9], [10] and (2) universal style transfer [3], [11], [12], [13].

The former explicitly studies the statistic correlations between content and style images in the deep feature space. Gatys et al. [7] propose the first flexible iterative optimization approach based on a pre-trained VGG19 network [14]. It can achieve arbitrary style transfer, but the forward and backward passes are time-consuming. STROTSS [10] replaces the I-1 style loss to Relaxed EMD distance to achieve higher visual quality. WCT [9] studies the second-order correlations via whitening and coloring transforms without costly optimization. To further reduce the computation of WCT, LT [3] uses linear transformations to approximate the matrix decomposition, resulting in real-time style transfer. Another direction on statistic optimization is to use attention mechanism [15] to explore spatial correlations. SANet [4] matches the content and style statistics via cross attention. AdaAttN [16] further explores the second-order attention to preserve more content information without losing style patterns. Most recently, Artflow [17] and VAEST [18] investigate the normalization flow [19] and VAE [20] to fuse style and content images, which also produce very promising results.

The latter focuses on zero- or first-order statistics for real-time style transfer. AdaIN [11] proposes Adaptive instance normalization to shift the deep content feature to the style space. Avatar-net [12] proposes to combine AdaIN [11] and style swap [21] to enhance the stylization in a coarse-to-fine manner. ReReVST [22] follows Avatar-net [12] to further develop inter-channel feature adjustment for both image and video style transfer. To handle high-resolution images, ArtNet [13] proposes Zero-channel Pruning to reduce model complexity. Wang et al. [23] propose Collaborative Distillation to compress the pre-trained network (e.g., AdaIN) for fast computation.

**Domain-aware style transfer.** The problem of arbitrary style transfer methods is that they learn style statistics from one reference image, which is not representative enough for the desired pattern. Domain-aware style transfer is to learn the robust statistics from many similar images so that it can transfer the most distinctive styles to the content images. The straightforward approach is to collect a number of desirable images to train a specific model for style transfer. For example, AST [1] proposes an artist-aware style transfer to achieve art stylization. In other words, they collect specific artworks as style references, e.g., Van Gogh, to train...
a network for specific style transfer. DualAST [24] follows this idea and proposes a more flexible deep network to balance both artwork style and artist style via Style-Control Block. Inspired by the study on the disentangled representation [25], domain-aware style transfer can also be regarded as an image2image problem where the image is factorized into class-related (style) and class-independent components (content). Kotovenko et al. [26] propose a double-GAN model to interpret the encoder and decoder for feature decomposition and stylization via two discriminators. [27], [28], [29] further investigate cross-cycle domain consistency for style transfer and other applications.

**Text-driven image style transfer.** Style transfer is a subjective topic, that is, different people may have different preferences for stylization. Using style images as references may not be as sufficiently good as texts can describe styles in a more abstract and aesthetic manner. The success of CLIP [30], VQVAE [31] and multimodality [32], [33], [34] show that text and image can be related via the shared projection space. Some pioneer works on image editing [35], [36], [37], [38], [39], [40], [41], [42], [43] and video understanding [44], [45], [46] show that language can be used for user-guided applications. [43] constructs open-ended vocabularies to flexibly recompose the visual content in the latent spaces of GANs. Most recently, [5] uses the CLIP as the condition for style transfer that increases the cross-correlation between the output and text description for text-guided style transfer. [2] further develops this idea by using both global and patch CLIP losses to generate high-resolution stylized images. Instead, in this work, we rely on the co-linearity between texts and images and train our model using contrastive similarity. Thus, both texts and images with the same style patterns can bring the stylization close to each other; otherwise, they push each other away.

### 3 Preliminaries

At the core of our proposed TeXT-driven image STyle transfer TxDT, there are two key components: CLIP [30] and Contrastive representation learning [47], [48]. In the following, we discuss how CLIP has been employed in this context in the past and how we use Contrastive representation learning to embed CLIP for artist-aware style transfer.

#### 3.1 styleCLIP

StyleCLIP [39] uses the text description only for arbitrary facial image editing, like adding mustache or glasses. The idea is to combine the generative power of styleGAN [49], [50] with the semantic abstraction of CLIP [30] to discover latent space attribute editing. StyleCLIP provides three options for achieving text-guided manipulation. The first two approaches directly optimize the CLIP-space distance between text and image, with dedicated models for desirable changes. Similar concepts are further developed by CLIPstyler [2], which takes augmented texts with the same meaning to iteratively optimize the network to produce reasonable stylizations. Figure 2 shows both processes of StyleCLIP and CLIPstyler. Given the target text $t_s$, their common goal is to optimize the distance $\Delta T$ to the generated image in the Clip space. Their difference is that StyleCLIP learns the generated image $G(\omega)$ from the latent code $\omega$, while CLIPstyler learns $f(I_c)$ from the source image $I_c$. The third approach disentangles the feature representation in the latent space to find the latent-code entries that induce both the image-space change and the global direction of the two text descriptions (source and target).

#### 3.2 simCLR

For text-driven style transfer, there is one key issue to address: ‘Is text rich enough to represent the key features?’ Text can explicitly describe the desirable styles, like *stormy night, colorful oil painting*, but usually it represents more abstract styles, like the name of artists (*Van Gogh*) or the name of art movements (*Impressionism*). These do not describe the visual styles. For StyleCLIP and CLIPstyler, they rely on the power of CLIP that it can capture the co-linearity between texts and images. When the training data are not sufficiently numerous or the training time is not enough, the quality of the generated images may become worse. The study on Contrastive representations learning [47], [48] provides an alternative to text-driven style transfer. Instead of learning dedicated mapping models for image generation, given priors of style texts, we learn to classify them in the CLIP space, hence arbitrary text-driven image style transfer can be achieved. In other words, we learn to maximize the prior estimation of text distribution on the CLIP space. As shown in Figure 2, by finding the principal direction, where the text features are projected on, that maximizing the distance
between different texts, we can learn the most distinct feature representation for each text. In the meantime, we use CLIP to minimize the distance between paired images and texts. We describe this mathematically as,

\[ L_{MC} = \min_{i=N,j=C} \Delta T - \max_{i=1,j=1} \Delta D \]

\[ = \min_{i=1,j=1} \sum_{i,j=N,j=C} \left( E_i(I_s^j), E_T(t_s^j) \right) + \min_{i=1,j=1} \sum_{i,j=N,j=C} \left( E_i(I_s^j), E_i(I_c^j) \right) \]

Equation (1) minimizes the intra-class distance \( \Delta T \) between paired images and texts, while maximizing the inter-class distance \( \Delta D \) between images from different classes. The maximization of inter-class distance can further be rewritten as minimizing the inter-class distance between images from the same classes.

4 APPROACH
4.1 Text for Style Transfer
Painting style, or painting language, represents the painting tastes of artists. It is a high-level abstract representation of the images. Previous style transfer methods \([4], [11], [13]\) use a referenced image to describe the desired painting style. The core idea of our approach is to describe painting style by means of texts, because of its convenience and flexibility. The benefits of the text model are twofold: (1) high-level style representation that avoids ambiguity caused by the image content; and (2) flexible adjustment with no effort for searching proper references. Recently developed text models, like CLIP \([30]\), motivate us to ask “Can text models be aware of different style representations?”

Following the discussion of Section 3, we believe that text and image can work interchangeably in the CLIP space for style transfer. In other words, text and image are comparable in the CLIP space and hence, they can both be used as style indicators. From the aspect of the style description, this co-linearity also exists between artists and their paintings, making it possible to realize artist-aware style transfer. To verify this, we make an analysis between images and style queries using a pre-trained CLIP model\(^3\). Initially, we collect a set of Artist-Painting pairs from WikiArt dataset \([51]\), as shown in Figure 3(a). To investigate the correlation between artists and paintings, the names of the artist are firstly tokenized and encoded to extract the feature \( E_T \in \mathbb{R}^{512} \). Next, we encode the paintings for the image feature \( E_i \in \mathbb{R}^{512} \). The correlation is then calculated by the dot product between the text \( E_T(t_s) \) and image features \( E_i(I_s) \). For each painting \( I_s \), we use the softmax function to find the probability score \( s \) for different artists \( t_s \), as follows:

\[ s(i,j) = \frac{\exp \left( E_i(I_s^j) \cdot E_T(t_s^j) \right)}{\sum_{j=0}^{N,j=C} \exp \left( E_i(I_s^j) \cdot E_T(t_s^j) \right)} \]

where \( C \) is the number of artists. A larger score \( s(i,j) \) means more likely the painting \( I_s \) is drawn by the artist \( t_s \). The relationship among scores is shown in Figure 3(b).

\[ t_s \text{.} \] It is clear that there are significantly larger values on the diagonal. Intuitively, we observe a strong correlation between the artists and their paintings in the CLIP feature space\(^4\).

4.2 Proposed text-driven image style transfer (TxST)

Figure 3 highlights that CLIP-based text and image features are colinear to each other for style transfer.\(^5\) Based on this finding, here, we introduce the architecture of our proposed TxST for artist-aware image style transfer. Figure 4 illustrates it.

Given content images \( I_c \) and desirable styles, artist’s name \( t_s \), and corresponding painting \( I_s \), TxST outputs the stylized image \( I_{cs} \). In the training stage, we use CLIP to maximize the variance of different styles by preserving the co-linearity between texts and style images. The network computes the contrastive similarity to minimize the inter-distance of the same styles. At test time, both text and image can be input as style indicators for arbitrary style transfer.

TxST consists of four parts: Image encoder, Image decoder, CLIP (text and image encoders), Positional mapper, and Polynomial attention. The structure of the image encoder is of the same structure as VGG-19 \([14]\), discarding the fully connected layers. The image decoder is symmetric to the image encoder, with gradual upsampling feature maps towards final stylized images. We use CLIP to encode the paired texts \( t_s \), \( i = 1, 2, ..., C \), where \( C \) is the number of artists. A larger score \( s(i,j) \) means more likely the painting \( I_s \) is drawn by the artist \( t_s \). The relationship among scores is shown in Figure 3(b). It is clear that there are significantly larger values on the diagonal. Intuitively, we observe a strong correlation between the artists and their paintings in the CLIP feature space\(^4\).

\[ t_s \text{.} \] There are two outliers in the figure, i.e., “P1-A6” and “P12-A5”. They indicate that the painting P1 by Berthe Morisot has the highest score to the painting of artist Monet(A6). The reason is that, both artists lived in the same country (France), and the artworks were created during the same artistic period (both were born in the 1840s) which we call it the Impressionism movement. For another outlier “P12-A5”, the painting from Wassily Kandinsky has similar styles to Jackson Pollock. Both paintings P5 and P12 in Figure 3(a) use geometric symbols in complex and abstract forms which are difficult to distinguish.

5. We also analyze the text-image relationship on textures and edges. The results are shown in the supplementary material.
of artists) and images ($I_s, i = 1, 2, ..., N$, where $N$ is the number of paintings) to obtain corresponding text features $E_T(I_s)$ and image features $E_I(I_s)$, respectively.

TxST uses CLIP features as the style condition to edit the content features. As shown in Figure 4, we process them by using Positional mapper to project it from 1-D vector to 2-D map, as $F_s = M(E_I(I_s^c))$. Then, the proposed Polynomial Attention module $P_R$ is used to fuse content and style features to obtain stylized features $F_{cs} = \sigma(F_s) \times P_R(\bar{F}_s, \bar{F}_c) + \mu(F_s)$, where $\bar{F}_s, \bar{F}_c$ are normalized content and style features, $\mu(F_s), \sigma(F_s)$ are mean and variance of the style features. Below, we introduce the proposed Positional mapper and Polynomial Attention module in details.

- **The positional mapper.** CLIP projects the image and text into 1-D vectors as $E_I(I_s, i) \in \mathbb{R}^{512}$ and $E_T(I_s) \in \mathbb{R}^{512}$, which will result in losing the spatial information for style transfer. Instead, to make style transfer **position aware**, we propose a Positional mapper to embed position information into the 1-D style vector, as shown in Figure 5. Following the study on relative position encodings [52], we design our positional mapper structure to introduce position information into the style vector. As shown in Figure 5, it first defines two learnable relative position encodings $R_h \in \mathbb{R}^{16 \times 1 \times 1 \times 512}$ and $R_w \in \mathbb{R}^{1 \times 16 \times 1 \times 512}$ for height and width, respectively. The two position encodings are repeated to the same size such that they add together for a relative position coding map $R \in \mathbb{R}^{16 \times 16 \times 512}$. The relative position map benefits the network to be aware of different locations on the spatial plane. Next, the position coding map attends the Self-Attention (SA) [53] process, as shown in Figure 5. During the SA process, the position coding map $R$ brings in relative distances between features into the style features at different locations, which expands the 1-D style vector into the 2-D plane $F_s \in \mathbb{R}^{16 \times 16 \times 512}$ at the same time. By using Positional mapper, we compute style transfer in the spatial domain to restore more complex visual patterns.

- **Polynomial attention module.** Using attention for style transfer has been studied in [4], [16]. The basic idea is to project style features onto the content features via cross attention. We further develop this idea as polynomial attention. In other words, we compute $i^{th}$ degree polynomial in style features to fit the non-linear correlations to the content. The computation of polynomial attention is shown in Figure 6. Specifically, we use multiple cross attention blocks to compute multiple polynomial attention between normalized content ($\bar{F}_c$) and $i^{th}$ order of style ($\bar{F}_s$) features. Finally, we use the mean and variance of style features ($\mu$ and $\sigma$) to denormalize the output. Mathematically, we have:

\[
F_{cs} = \sigma(F_s) \cdot P_R(\bar{F}_s, \bar{F}_c) + \mu(F_s) \text{ where } P_R(\bar{F}_s, \bar{F}_c) = \bar{F}_c + \sum_{i=1}^{R} \text{Softmax}\left(\frac{Q[\bar{F}_s] \times K[\bar{F}_c]}{\sqrt{d}}\right) V[\bar{F}_s] \tag{3}
\]

where $R$ is the highest order of style estimation, $d$ is the dimension of the feature maps, $Q$, $K$ and $V$ are $1 \times 1$ convolution for query, key and value. The study on the polynomial attention has the same spirit as polynomial regression estimation. The merits of it are twofold: (1) it learns higher-order correlations between content and style images for better approximation, and (2) it adapts to the larger variance of the style features for unbiased prediction.

4.3 Loss functions

- **Directional CLIP loss.** To guide the content image following the semantic of the target text (artist’s name), we use directional CLIP loss [2], [36] to align the CLIP-space direction between the text-image pairs of target $t_s$ and output $I_{cs}$. It is defined as:
is to compute the feature similarity between stylized results in Equation (5), there are two terms for the loss: The first one
as both content and style input to extract the stylized feature output images (pink/yellow/green dots around red dots).
Therefore, we guide the model to minimize the intra-class distance between different art collections painted by the
same painter, as well as maximizing the inter-class distance between different painters.

• CLIP feature loss. Studied by Johnson et al. [54], using pre-trained VGG to extract VGG features for content and
style images can minimize L2-norm distance between them to encourage stylized output with visual patterns close to
the style images. Inspired by it, we propose to use the CLIP feature loss to guide the stylization close to the style feature
representation. We define it as:

\[
L_{\text{clip}} = \frac{1}{N} \| \nu_i - \nu_j \|^2_2
\]

• Content and style feature loss. Following the existing style transfer methods [4], [16], [18], we employ content and
style feature loss by using the pre-trained VGG network to minimize the distance in the deep feature space as:

\[
\begin{align*}
L_{\text{sty}} &= \sum_{i=1}^{N} \| \mu(W_s^i(I_{cs})) - \mu(W_s^i(I_s)) \|^2_2 \\
&+ \sum_{i=1}^{N} \| \sigma(W_s^i(I_{cs})) - \sigma(W_s^i(I_s)) \|^2_2 \\
L_{\text{con}} &= \sum_{i=1}^{N} \| W_s^i(I_{cs}) - W_s^i(I_c) \|^2_2
\end{align*}
\]

Algorithm 1 Training procedure for TxST

Input:
1: Network Initialization, fix CLIP and VGG;
2: batch size N, input content image I_c, artist’s name t_s and painting I_s;

Output: I_{cs}

3: for sampled minibatch \{I_i\}_{i=1}^{N} do
4: \hspace{1em} for All \(i \in \{1, ..., N\}\) do
5: \hspace{2em} randomly draw two paintings from the same artist (t_s^i) as I_s and I_s^i; random augment artist’s name t_s and I_s^i;
6: \hspace{2em} compute stylized output I_{cs} and I_{cs}^i;
7: \hspace{1em} end for
8: \hspace{1em} for All \(i \in \{1, ..., N\}\) and \(j \in \{1, ..., N\}\) do
9: \hspace{2em} compute \(S(v_s^i, v_s^j)\) and \(S(v_s^i, v_s^j)\); 
10: \hspace{2em} end for
11: \hspace{1em} compute contrastive similarity loss as Equation (5), and also other five losses for the final loss;
12: \hspace{1em} end for
13: return TxST

We use VGG-19 [14] to extract \(W_s\) features (relu1_2, relu2_2, relu3_4, relu4_1) to compute the style loss, where \(\mu\) and
\(\sigma\) are the mean and variance operators. We also extract \(W_c\) features (relu2_2, relu3.4) to compute the content loss.
Furthermore, identity loss \(L_{\text{id}}\) is also used to preserve more content information. The process is to take the target image
as both content and style input to extract the stylized feature \(F_{cs}\), then compute the \(L_1\)-norm distance to the content
feature \(F_c\) as \(L_{\text{id}} = \| F_{cs} - F_c \|_1 \).
• Total loss. We train the network using all pre-defined losses. Hence, we define the final loss as $L = \lambda_{clip}L_{clip} + \lambda_{clipj}L_{clipj} + \lambda_{sim}L_{sim} + \lambda_{sty}L_{sty} + \lambda_{con}L_{con} + \lambda_{id}L_{id}$, where $\lambda_{clip}$, $\lambda_{clipj}$, $\lambda_{sim}$, $\lambda_{sty}$, $\lambda_{con}$ and $\lambda_{id}$ are coefficients to balance these loss components. The whole training procedure is summarized in Section 1.

5 EXPERIMENTS
5.1 Implementing Details
• Training strategy. To achieve better visual quality, we use the VGG-19 [14] pre-trained on the ImageNet dataset as the Image Encoder and fix its parameters. Then, we train TxST in two stages: (1) We built an auto-encoder structure with the Image Encoder and Image Decoder (i.e., the orange box in Figure 4), and train the Image Decoder for image reconstruction. (2) We add the Positional mapper and Polynomial attention module to train the whole network for style transfer, using pre-trained Image Encoder and Decoder.
• Datasets. We use the images from MS-COCO [55] (about 118k images) for the image reconstruction task in the first training stage. In the second training stage, we train TxST with MS-COCO [55] as our content image set and WikiArt [51] (about 81k images) as the style image set. In the training phase, we load the images with the size of $512 \times 512$ and randomly crop as training patches of size $256 \times 256$. As data augmentation, we randomly flip the content and style images. For inference, our TxST can handle the images with any resolutions. In this Section, we use the images with $512 \times 512$ resolution for fair comparison. We also use WikiArt_subset [1], a subset from WikiArt, to compare artist-aware style transfer. It contains 13 artists and each artist has 40-200 paintings.
• Parameter setting. We train TxST using Adam optimizer with the learning rate of $1 \times 10^{-4}$. The batch size is set to 30 and TxST is trained for 100k iterations (about 8 hours) on a PC with two NVIDIA RTX3090 GPUs using PyTorch deep learning platform. The weighting factors in the total loss are defined as: $\lambda_{clip} = 100$, $\lambda_{clipj} = 50$, $\lambda_{sim} = 10$, $\lambda_{sty} = 5$, $\lambda_{con} = 1$, $\lambda_{id} = 2$.
• Metrics and evaluation. Following VAEST [18] and LT [3], we estimate the content loss and style loss (Equation (7)) for VGG score comparison. We also conduct CLIP score estimation, CLIP loss (text/image-cosine similarity) [2] to measure the semantic similarity between the target texts/images and stylized images. For artist-awareness, we follow AST [1] to compute the style transfer deception rate, which is calculated as the fraction of generated images which are classified by the VGG-16 network as the artworks of an artist for which the stylization was produced. Higher value means closer to the artist style.

5.2 Comparison with the Arbitrary Style Transfer Methods
Benefited from CLIP, the style clue of our TxST can be either image or text. The arbitrary style transfer methods [4, 9, 11, 16, 17, 18, 56] usually use style images to provide guidance for style transfer. We collect 20 content images and 20 style images to form 400 image pairs for image-driven arbitrary style transfer in this section. To demonstrate the effectiveness of TxST on arbitrary style transfer, we use reference images to provide style clues for all methods. We compared TxST to seven state-of-the-art arbitrary style transfer methods, including WCT [9], AdaIn [11], SANet [4], ArtFlow [17], AdaAttN [16], DSTN [56], and ST-VAE [18].

### Table 1
Comparison with the SOTA arbitrary style transfer methods. (Red: best, Green: the 2nd best, and Blue: the 3rd best)

| Method         | VGG Score | CLIP Similarity Scores |
|----------------|-----------|------------------------|
|                | Style↓    | Content↓               | Style↑ | Content↑ |
| WCT [9]        | 74.11     | 197.26                 | 0.487  | 0.729    | 0.584 |
| AdaIn [11]     | 167.53    | 123.02                 | 0.642  | 0.599    | 0.620 |
| SANet [4]      | 104.41    | 153.65                 | 0.541  | 0.700    | 0.611 |
| ArtFlow-AdaIN  | 149.98    | 138.59                 | 0.578  | 0.647    | 0.611 |
| AdaAttN [16]   | 83.45     | 119.28                 | 0.658  | 0.604    | 0.630 |
| DSTN [56]      | 122.34    | 130.11                 | 0.616  | 0.663    | 0.638 |
| ST-VAE [18]    | 108.73    | 139.23                 | 0.635  | 0.581    | 0.606 |
| Ours           | 99.36     | 82.72                  | 0.637  | 0.791    | 0.706 |

Table 1 shows the results of the quantitative comparison, while Figure 7 illustrates the quantitative comparison. WCT [9] utilizes the whitening and coloring transforms to the content features to match the statistical distribution of the style features. We observe that WCT [9] has the lowest style loss (74.11) and the highest style similarity score (0.729) to the style image. The best style scores suggest that WCT is good at handling global style synthesis. However, WCT lacks attention to details. The visualization in Figure 7 clearly shows the results produced by WCT have many improper style patches, and the contents are distorted significantly (see 2nd, 3rd and 4th rows). Consequently, this
Fig. 7. Comparison among image-driven arbitrary style transfer methods. Our results have a good balance between the contents and styles with clear semantic information from the content image and painting preference from the style image. Please zoom in for better view.

Fig. 8. Deception rate for different artists. We show the deception rate on each artist from WikiArt subset. Our method achieves the best performance on all artists.

leaves to lower content performance with a content loss of 197.26 and a content similarity score of 0.487. AdaAttN [16] has the best content similarity score of 0.658. Compared to WCT, the stylizations of AdaAttN have clearer contents as shown in Figure 7, but they are limited in expressing target major color changes and texture synthesis. For instance, the background of the bus (see 1st row) should be dominated by blue, and the texture of the clock is not clear (see 5th row). Instead, our TxST successfully transfers the target style well, and preserve the salient content at the same time. As shown in Figure 7, our stylized results clearly show the contents like that in AdaAttN (see the bus in 1st row, the motorcycle in 2nd row), while the style stays on par with WCT’s and SANet’s. Besides, the second row of Figure 7 shows that the result with TxST sufficiently reflects the semantic of the content image, and expresses the painting preference of the style image (like a woodblock painting). Quantitatively, our approach achieves the best balanced performance with an average F1 score of 0.706, as shown in Table 1.

5.3 Artistic Style Transfer

Artistic styles are more complex, abstract and diverse. It is difficult to have one reference image to represent the artist’s signature style. One of our key claims is to learn artistic styles using specific artists’ names. To show the ability of our proposed approach, we fine-tune TxST on the WikiArt subset used in AST [1], which contains 13 artists of different styles. We also compare it to the recent text-driven style transfer CLIPstyler. For text-driven style transfer, we use the names of the 13 artists as style description (denoted as $T_s$). Then, following the design in [2], we train CLIPstyler with fast and optimized schemes, and denote them as CLIPstyler(fast) and CLIPstyler(opti).

Quantitative Comparison. Here, we measure the similarity to the content and artist in the CLIP feature space using
Fig. 9. **Comparison among text-driven artist-aware style transfer methods.** We show six examples (content images in red boxes) using three different methods: AST [1], CLIPstyler [2] and ours. We use names of painters as text prompts for style transfer. For reference, we also list some representative paintings in blue boxes for comparison. Styles of artists are very abstract and subjective. We highly recommend readers to check each artist online or from our supplementary files for better comparison.

**Table 2**

| Method                  | Clip Scores | Deception Rate† |
|-------------------------|-------------|-----------------|
| AST [1]                 | Content†   | 0.338           | 0.269               |
| CLIPstyler(fast) [2]    | Style†     | 0.736           | 0.378               |
| CLIPstyler(opti) [2]    | F1†        | 0.538           | 0.469               |
| Ours                    |             | 0.624           | 0.428               |
|                         |             | 0.678           | 0.418               |

The CLIP scores defined in Equations (8) and (11), and compute the F1 score accordingly. For artist-awareness, we follow AST [1] to compute the style transfer deception rate. Specifically, we use a trained VGG-16 model to classify the transferred images into different artists, where the classification accuracy is denoted as the deception rate. A higher deception rate means the transferred images have better artist stylization.

\[
s_{style}(T_s, I_{cs}) = \frac{E^{I}_{T_s} \cdot E^{I}_{cs}}{\|E^{I}_{T_s}\| \times \|E^{I}_{cs}\|}
\]

where \(T_s\) denotes the style description in the form of text.

Table 2 reports the results. We observe that CLIPstyler(fast) leads to the best content similarity score (0.736); however, the transferred images have poor artistic style performance, with a deception rate of 0.469. The results of AST have the second-best deception rate of 0.664, but the similarity to the content image is of 0.538. CLIPstyler(opti) has the best CLIP scores, but achieves the worst deception rate. This is expected, since CLIPstyler(opti) requires dedicated training for each individual content and style dataset. It will optimize the CLIP scores as its loss function. However, it also introduces bizarre patterns (as shown in Figure 1 and 9) into the stylization. The results are not consistent to each specific style. Instead, our TxST provides a good balance to the style and content, reaching the second-best performance on CLIP scores and the best performance on the deception rate, which demonstrates its efficiency and effectiveness. We also note that AST, CLIPstyler(opti) and CLIPstyler(fast) train different models for different artists; in contrast, our TxST is used for arbitrary style transfer, which is more flexible for applications. Figure 8 also shows the class-specific accuracy of deception rate. We clearly observe that using our TxST (red bars) achieves dominant performance on all artists.
User study. Since artistic styles are very subjective, we also conduct a user study for subjective evaluation. We invite users from different backgrounds, like art, design, literature, and science, to ensure the study as fair as possible. The questionnaire compares the painting styles of eight artists from the WikiArt subset. For each artist, we collect the results from AST [1], CLIPstyler(opti) [2], and the proposed TxST by using three different content images. In each question, the users were given three results from the same content image by using the three methods. Besides the artists’ names, we provide users with three representative artworks from the artist as references. The users are requested to rank the style similarity to the artist, where 3 denotes the most similar, and 1 means the most different. We then average the scores from all users as the Mean Opinion Score (MOS). The results are shown in Figure 11. We observe that TxST achieves the highest average MOS of 2.31, which suggests that our results have the most similar painting style to the target artists at a perceptual level.

Qualitative Comparison. Figure 9 shows the visual comparison of different methods for artist-aware style transfer. There are six content images in red boxes and six artists’ names for style transfer. Note that AST is an optimization based approach that learns a dedicated model for every artist. It does not require any name as text input. For CLIPstyler and TxST (ours), we use artists’ names as textual style to guide stylization. For reference, we also show three representative paintings in blue boxes for six artists. Our findings are summarized as: First, our results show comparable or even better content preservation ability as compared to AST and CLIPstyler. For instance, like CLIPstyler, TxST can restore structural information, like buildings. It can also preserve the fine textures, like the strides on zebras. Second, TxST can faithfully mimic the signature styles from specific artists. For example, our approach can “copy” the fruit patterns from Paul Cezanne, especially the color tone and temperature, while other approaches fail. Moreover, TxST can transfer painting curvatures, like the distorted curves in El-Greco and Van Gogh, and can learn the color mosaic from Ernst Kirchner. On the other hand, AST and CLIPstyler (both fast and optimal versions) do not reveal the key features of artists, like zebras in Pablo Picasso style and buildings in Jackson Pollock style. Third, compared to CLIPstyler, TxST can maximize the visual differences among different artistic styles (this is further discussed in Section 5.4). Finally, TxST is a universal style transfer without requiring neither dedicated training for each style (as AST and CLIPstyler(last)) nor extra online training efforts (as CLIPstyler(opti)).

5.4 Ablation Study
To confirm the effectiveness of each component of TxST, we conduct several ablation studies.

- Loss terms. First, as introduced in Section 4.3, we have six different loss terms for training. Content loss, style loss and identity loss, which are widely used in style transfer to encourage stylization. The key terms are Contrastive similarity loss ($L_{sim}$), Directional CLIP loss ($L_{clip}$) and CLIP feature loss ($L_{clip_f}$). To evaluate their effects, we use the 13 artists’ names from WikiArt_subset as input for text based style transfer. Our metrics include content loss, VGG feature loss between content and stylized images (as $L_{con}$ in Equation (7)), text CLIP loss (Equation (11)) and content CLIP loss (Equation (8)).

Table 3 shows the results when training with different losses. Baseline is the model that uses content ($L_{con}$), style ($L_{sty}$) and identity losses ($L_{id}$) and compare it with different...
loss combinations. We observe that using both Contrastive similarity loss ($L_{sim}$) (3rd row) and Directional CLIP loss (2nd row) reduces the text CLIP loss, which indicates that they can guide the stylization close to the target text description. Meanwhile, using CLIP feature loss ($L_{clip}$) (4th row) reduces the content loss and content CLIP loss approximately by 0.05 and 0.1, respectively, but it also increases the text CLIP loss. The last row is our TxST full TxST model that combines all loss terms. Obtaining the best results is a balance between content and text styles.

- **Polynomial attention module.** TxST introduces the polynomial attention module to explore high-order correlations between content and style features, hence it generates images with styles closer to the style references. As described in equation (3), we can compute the cross correlation from the 1st to nth order features. To quantitatively decide the optimal polynomial setting, we use 20 style images as reference and 20 content images as target for image based style transfer. To demonstrate its effectiveness, we compute different metrics and report their results in Table 4.

| Order of Attention | VGG Score |
|--------------------|-----------|
|                    | Style↓ | Content↓ | Style↑ | Content↑ | F1↑ |
| 1st order          | 100.28 | 91.05    | 0.612  | 0.683    | 0.648 |
| 2nd order          | 99.36  | 82.72    | 0.37   | 0.791    | 0.706 |
| 3rd order          | 100.41 | 84.40    | 0.620  | 0.787    | 0.693 |
| 4th order          | 101.97 | 84.74    | 0.618  | 0.797    | 0.696 |
| 5th order          | 103.00 | 87.99    | 0.616  | 0.717    | 0.663 |

Specifically, in Table 4 we compare both VGG based losses and CLIP based losses. Compared to the 1st order model, using other polynomial models higher than 1st order improves both content and style performance, except the 5th order (last row), which indicates that using higher order polynomial can indeed improve the overall performance, but it may also drop after reaching the optimal point. This is expected, since higher-order models mean more detailed regressive modelling, but they can also overfit the correlation between content and style images. Moreover, we observe that using higher order polynomials reduces the style loss, but it also increases the content loss. This is the trade-off between content and style, as discussed in [3], [13], [16], [17]. For practical applications, we use the 2nd polynomial model for its good balance between content and style (higher F1 score compared to others).

- **Analysis on the diversity of artist-aware style transfer.**

All quantitative and qualitative comparisons so far demonstrate that TxST generates stylized images with better visual quality than the state of the art. Here, however, we answer the question whether ‘styles of different artists are well separated to each other’?

To analyze the style diversity of TxST, we use t-SNE [58] to process both content and stylized images and check the data scatters or the distribution. The basic process is: first, we use CLIP to extract feature codes for content images ($E_I(I_c)$), style texts ($E_T(t)$) and stylized images ($E_I(I_{st})$). Second, we use t-SNE to project the codes into the 2-D space and draw them on an x-y plane for visualization.

In Figure 12, we show both style texts (symbol “X”) and images (symbols “.”). Dots in different colors represent different images. We make three observations: (1) the style texts are well separated in the 2-D space, which indicates that CLIP has the ability to distinguish different style descriptions. (2) By comparing Figure 12 (a) to Figure 12 (b) and (c), we observe that the stylized images are well scattered around the space. This indicates that the stylization is successful for images, as even two different stylization results applied to the same initial image can be pushed away. (3) By comparing Figure 12 (b) to Figure 12 (c), we observe that using the model trained on WikiArt already distinguishes different styles; however, using the model trained on WikiArt_subset can push the images even further from each other.

Furthermore, Figure 13 displays more examples of artist-aware style transfer, thus corroborating style diversity. We observe that TxST successfully grasps the key features of different artists and transfers them to the content images. The differences among different artists are significant. For example, artists A. J. T. Monticelli, Constantin Guys, Jean Leon Gerome and Leon Bonnat are from the late 18th to the early 19th century, when the main trend was religious painting and the painters used natural lighting and shadows to describe the sense of space. Painters like Andy Warhol, Bridget Riley, Joan Mitchell are contemporary artists. They are bold and experimental. They usually use more colorful pigments, wild and rough curves and lines to paint their feelings. We also note some distinguish oriental styles from Utagawa Toyokuni, who is one of the painters from the Ukiyo-e moment in Japan. For other painters, we encourage the readers to check more information from the WikiArt website [https://www.wikiart.org/].

### 5.5 Interactive Text-driven style transfer

TxST leads to flexible universal text-driven style transfer. The texts can be general descriptions like texture patterns, color distributions and objects. Moreover, it can achieve multiple style transfer by using texts; here, we explore this.

- **General style transfer.** TxST can take arbitrary texts as input for style transfer. The texts can describe objects or colors, like red apples and colorful rainbow. To achieve this, we slightly fine-tune TxST using smaller weights on the CLIP
loss (Equation (4)) so that the model is more sensitive to the changes of texts. Note that TxST is still trained on the WikiArt dataset without using any extra labeled texts or images, hence the model is general to some extent. For any specific text, it still requires more dedicated training.

For this, we test the content image using texts to describe different styles, like colors (blue sea, green crystal), textures (white wool, colorful chessboard) and visual appearance (rough sketch with black pen, neon light, dark night). Figure 14 illustrates the results. We observe that TxST successfully transfers the target styles to the content images.

- **Multiple style transfer.** TxST can also achieve multiple style transfer. Unlike previous works [11], [18], it does not require multiple reference images for style fusion; instead,
From the CLIP space and produce aesthetics close to the artists’ works. TxST also points a new direction to text-driven style transfer. Future work includes combining images, texts, and other cues to deliver a more flexible user-guided style transfer.

\section{Conclusion}

In this paper, we proposed a text-driven approach for artist-aware style transfer, coined TxST. Unlike most style transfer methods, TxST can use either images or texts as style references for the desired stylization. The polynomial attention module and CLIP-space-based contrastive similarity training of TxST enable exploring the co-linearity between texts and images without requiring costly data collection and annotation. We conducted comprehensive experiments on both general and artist-specific style transfer, using either images or text as style references. Extensive results show that TxST achieves perceptually pleasing arbitrary stylization, revealing its ability to extract critical representations from the CLIP space and produce aesthetics close to the artists’ works. TxST also points a new direction to text-driven style transfer. Future work includes combining images, texts, and other cues to deliver a more flexible user-guided style transfer.

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