

# StylerDALLE: Language-Guided Style Transfer Using a Vector-Quantized Tokenizer of a Large-Scale Generative Model

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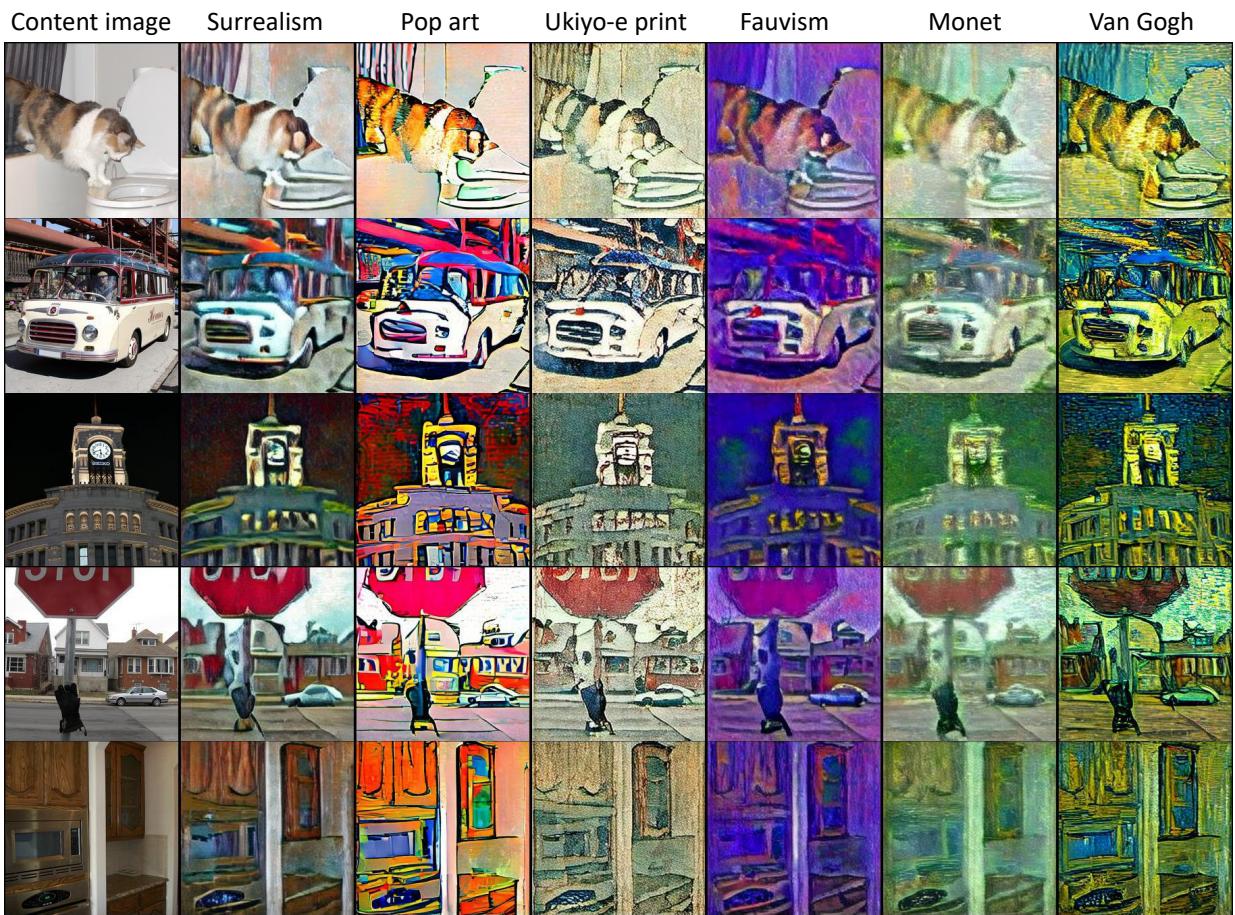


Figure 1: With a large-scale pretrained vector-quantized tokenizer (e.g., the dVAE of DALL-E) and CLIP, StylerDALLE can transfer various types of styles (indicated on the top), from abstract art styles to specific artist styles and more.

## Abstract

Despite the progress made in the style transfer task, most previous work focus on transferring only relatively simple features like color or texture, while missing more abstract concepts such as overall art expression or painter-

specific traits. However, these abstract semantics can be captured by models like DALL-E or CLIP, which have been trained using huge datasets of images and textual documents. In this paper, we propose StylerDALLE, a style transfer method that exploits both of these models and uses natural language to describe abstract art styles.

*Specifically, we formulate the language-guided style transfer task as a non-autoregressive token sequence translation, i.e., from input content image to output stylized image, in the discrete latent space of a large-scale pretrained vector-quantized tokenizer; e.g., the discrete variational auto-encoder (dVAE) of DALL-E. To incorporate style information, we propose a Reinforcement Learning strategy with CLIP-based language supervision that ensures stylization and content preservation simultaneously. Experimental results demonstrate the superiority of our method, which can effectively transfer art styles using language instructions at different granularities. Code is available at <https://github.com/zipengxuc/StylerDALLE>.*

## 1. Introduction

In the last few years, a lot of work has focused on the style transfer task using a *reference image* as a representative of the target style, where the goal is to transfer the style of the reference to a content image [14, 16, 28, 3, 22, 8, 9, 40]. Recent improvements in this field include: reducing the artifacts [2, 25, 5, 40], modeling the style-content relationship [28, 43, 24], increasing the generation diversity [21, 37, 46] and many others. However, art styles are usually abstract concepts, e.g., pop art, fauvism, and the style of Van Gogh. To transfer these abstract art styles to a content image, the low-level features (e.g., textures and colors), which are commonly extracted from a single reference image, are not enough. A possible solution is to collect a set of reference images that can be used, e.g., to train a Generative Adversarial Network (GAN) for artist-specific style transfer [36, 47, 19]. The disadvantage of this *set-based representation* is the effort required to collect sufficiently large style-specific data for training.

Recently, large-scale image generative models [32, 31, 35, 45] have shown their power to generate high-quality images of various types, e.g., realistic photo, cartoon, ukiyo-e print, or painting of a specific artist. Moreover, CLIP [30], which is trained with 400 million text-image pairs, learns good joint knowledge between language and vision. Can we leverage the power of these large-scale models for style transfer? In this paper, we propose StylerDALLE, a language-guided style transfer method that uses both the vector-quantized tokenizer of large-scale image generative methods and CLIP. There are three advantages of our method. Firstly, as compared to images, language is a more natural and efficient way to describe abstract art styles and enables more flexibility. Language can directly indicate art styles at different levels, e.g., “*Van Gogh style oil painting*” and “*Van Gogh starry night style oil painting*”. Secondly, using CLIP and the language description of style saves the effort of collecting style images, as CLIP already learns style-related knowledge and thus can be used to provide

supervision. Thirdly, using a large-scale pretrained vector-quantized tokenizer potentially enables style transfer results to be closer to real artworks, as the model is trained from an enormous number of real-world images. In concrete, we propose a Non-Autoregressive Transformer (NAT) model [15], which translates tokens of a content image to tokens of a stylized image in the discrete latent space of a pretrained visual tokenizer, and a two-stage training paradigm.

First of all, since both the input content image and output stylized image can be represented by a sequence of tokens via the large-scale pretrained vector-quantized tokenizer, we formulate the language-guided style transfer task as a token sequence translation. Specifically, we design a NAT model that learns to translate a token-based representation of a low-resolution image into a full-resolution representation, where the final token sequence contains appearance details specialized for the target style. The most important advantage of using NAT in image generation, with respect to the more common autoregressive transformer (AT) based generation, is that NAT is much faster than AT at inference time, as it allows a *parallel* token generation while AT generates in a token-by-token way.

Secondly, we propose to use CLIP-based language supervision to ensure stylization and content preservation simultaneously, saving the effort to collect data and design dedicated losses. A similar solution that uses CLIP to do style transfer is CLIPStyler [20]. Since merely maximizing the CLIP similarity with respect to a textual style description is not enough for a style transfer task, which should also *preserve* the content of the source image, CLIPstyler introduces a hybrid of losses, including a content loss measured in an external pre-trained VGG network. Conversely, we propose an alternative direction, which avoids the need to tune the coefficients of different loss functions so as to keep the balance between style and content. Specifically, we introduce a two-stage training paradigm: 1) a self-supervised pretraining stage, where the model learns to add semantically coherent image details from a low-resolution image to a high-resolution image; and 2) a style-specific fine-tuning stage, where the model learns to incorporate style into the high-resolution image. Since the fine-tuning phase is built on top of the first stage, the translator is able to keep the semantic consistency with respect to the input image as learned during pretraining. Moreover, we create a textual prompt by concatenating both the style and the textual description of the image content (i.e., its caption). This way, the prompt simultaneously models both the target appearance (i.e., the style description) and the image content which should be preserved by the translation process. Finally, since our translator’s output is discrete and there is no ground-truth tokens for a stylized image, we introduce a Reinforcement Learning (RL) approach to fine-tune the translator using a reward based on the CLIP similarity be-

tween the stylized image and textual prompt, enabling the model to explore the answers in the latent space of a pre-trained vector-quantized tokenizer.

We call our network **StylerDALLE** and we show that it can generate stylized images driven by different types of language guidance. Compared with previous language-guided and reference image-based transfer methods, our generated images are less inclined to produce artifacts or semantic errors. Moreover, they can capture abstract concepts related to the target style (e.g., the typical brushstrokes of the artist) besides low-level features like texture and colors. We illustrate the effectiveness of our method through qualitative results, quantitative results, and a user study.

To conclude, our main contributions are:

- We propose **StylerDALLE**, a language-guided style transfer method that manipulates the discrete latent space of a pretrained vector-quantized tokenizer using a token sequence translation approach.
- We propose a non-autoregressive translation network that translates a low-resolution content image into a full-resolution image with style-specific details.
- We propose a two-stage training procedure, including an RL strategy to ensure stylization and content preservation using CLIP-based language supervision.
- Experimental results show that **StylerDALLE** can effectively transfer abstract style concepts, going beyond simple texture and color features while simultaneously preserving the semantic content of the translated scene.

## 2. Related Work

**Reference Image-Based Style Transfer.** Gatys et al. [14] propose a neural style transfer method in which a pre-trained CNN is used to extract content and style information from images, and to transfer the latter from an image to another. Following this pioneering work, a lot of interests have been attracted, with different methods focusing on different aspects of the topic, such as, e.g., diversified style transfer [37, 41], or attention mechanisms to fuse style and content [44, 28, 24]. A specific line of work focuses on artistic style transfer. For instance, Chen et al. [3] propose to use internal-external learning and contrastive learning with GANs to bridge the gap between human artworks and AI-created artworks. Wang et al. [40] introduce an aesthetic discriminator trained with a large corpus of human-created artworks. Other works train GANs using an artist-specific collection of images [36, 19, 4]. In contrast, we use the generic visual-language semantics embedded in the large-scale pretrained vector-quantized tokenizer and CLIP to avoid collecting style or artist-specific datasets.

**Language-Guided Style Transfer.** Very recently a few works have proposed transferring methods conditioned on a textual description of the style. For instance, Fu et al. [12] use contrastive learning to train a GAN for artistic style transfer, but they adopt descriptive language instructions rather than more abstract style concepts. Gal et al. [13] use the CLIP space for a domain adaptation of a pre-trained StyleGAN [17]. The method closest to our approach is CLIPStyler [20], where a patch-wise CLIP loss is used to train a U-Net [34]. However, to condition the style change while preserving the image content, CLIPStyler uses hybrid losses and a rejection threshold, introducing many hyperparameters. In our method, we only use CLIP-based language supervision to ensure the style and content, saving the efforts of designing losses and tuning hyperparameters.

**Large-scale Text-to-Image Generation Models.** Recently, text-to-image models trained with large or very large scale datasets [32, 31, 35, 45, 1] have attracted tremendous attention because of their excellent performance in generating high-quality images starting from a textual query. Inspired by their strong ability to synthesize various types of images, we study how to use large-scale text-to-image models for style transfer. Specifically, we focus on transformer-based methods, which are potentially less time-consuming as compared to diffusion model-based methods [26]. In addition, we propose to use a non-autoregressive transformer that can generate tokens in parallel.

## 3. Background

**Vector-Quantized Image Tokenizer.** Transformer-based text-to-image generative models [32, 10, 11, 45, 1] rely on a vector-quantized image tokenizer to produce a discrete representation of the images, e.g., DALL-E [32] has a dVAE [33] and PARTI [45] has a ViT-VQGAN. Despite the differences in implementing the tokenizers, the effects are the same. In more detail, an image  $I$  is transformed into a  $k \times k$  grid of tokens  $X = \{x_{i,j}\}_{i,j=1,\dots,k}$ , using an encoder  $E(\cdot)$ . Each token  $x_{i,j} \in X = E(I)$  is an index of a codebook of embeddings ( $C = \{\mathbf{e}_1, \dots, \mathbf{e}_M\}$ ,  $1 \leq x_{i,j} \leq M$ ), built during the training, and corresponds to a patch in  $I$ . A decoder  $G(\cdot)$  takes as input a grid of embeddings and reconstructs the original image:  $\hat{I} = G(\{e_{x_{i,j}}\}_{i,j=1,\dots,k})$ . Training in the transformer-based text-to-image generative models consists of two stages. The first stage is dedicated to training the image tokenizer, while in the second phase, a transformer is used to learn a prior distribution over the text and the image tokens. In **StylerDALLE** (Sec. 4) we only use the pretrained image tokenizer.

**Non-Autoregressive Transformer (NAT).** Gu et al. [15] propose a NAT for natural language translation, which con-

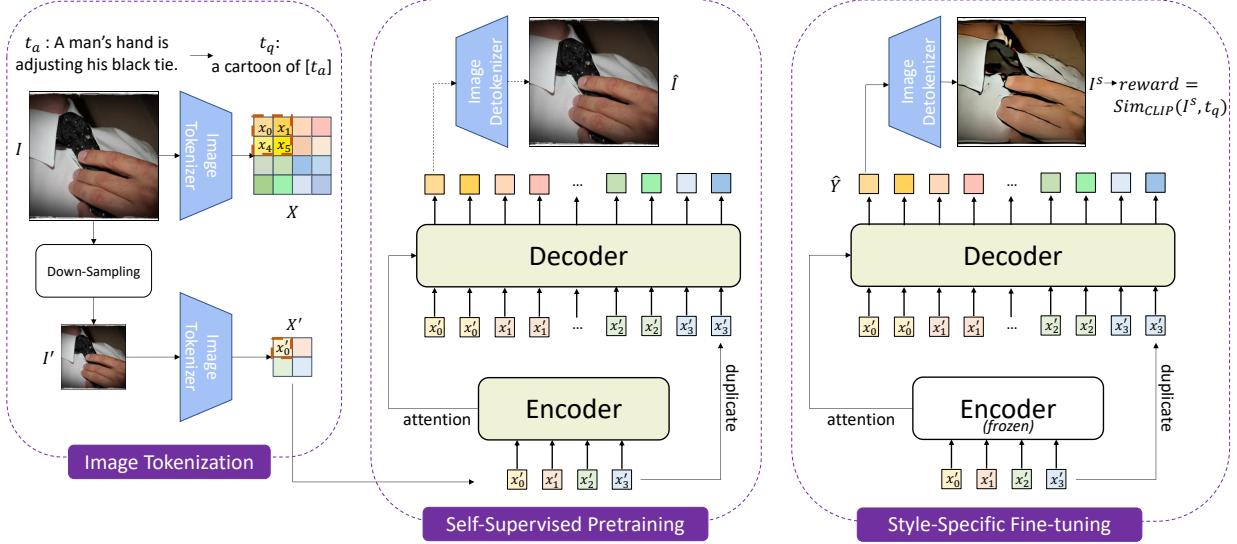


Figure 2: A schematic illustration of StylerDALLE. We propose a NAT to translate tokens of a half-resolution *content* image to tokens of a full-resolution *stylized* image. StylerDALLE consists of three parts: 1) image tokenization preprocessing, to obtain the discrete visual tokens from a pretrained image tokenizer; 2) self-supervised pretraining, to train the NAT to predict full-resolution content images from half-resolution content images; and 3) style-specific fine-tuning, to let the model adding style details in the up-scaling prediction via Reinforcement Learning with language-prompted CLIP guidance. Specifically, in our NAT, the decoder input is duplicated from the tokens of the half-resolution image, following the natural positional correspondence (as highlighted by orange rectangles in the left part) with the full-resolution image.

sists of an encoder and a decoder. The encoder takes as input a source sentence  $X = \{x_1, \dots, x_{N'}\}$  of  $N'$  tokens and outputs a distribution over possible output sentences  $Y = \{y_1, \dots, y_N\}$ , where  $Y$  is the translation of  $X$  in the target language and, usually,  $N \neq N'$ . The main novelty of NAT with respect to AT is that, during training, NAT uses a *conditional independent* factorization for the target sentence and the following log-likelihood:

$$\mathcal{L}(\theta) = \sum_{n=1}^N \log p(y_n | x_{1:N'}; \theta), \quad (1)$$

which differs from the common AT factorization in which the prediction of the  $n$ -th token ( $y_n$ ) depends on the previously predicted tokens ( $p(y_n | y_{0:n-1}, x_{1:N'}; \theta)$ ). This conditional independence assumption makes it possible a *parallel* generation of  $Y$  at inference time, largely accelerating the translation time with respect to AT models. Importantly, to make parallel generation possible, the encoder input ( $X$ ) is provided as input to the decoder as well, and individual tokens ( $x_n \in X$ ) can be copied zero or more times, with the number of times each input is copied depending on a specific predicted “fertility” value. As we will see in Sec. 4.1, we do not need to predict fertilities because, in our case, the cardinality of the input copies is fixed and determined by the up-scaling task we use for the image translation.

## 4. Method

The language-guided style transfer task can be described as follows. Given an image  $I$ , we want to generate a new image  $I^s$  which preserves the semantic content of  $I$  but changes its appearance according to a textual style description  $t_s$  (e.g., “cartoon”). In StylerDALLE, we formulate this task as a *visual-token based translation*, from tokens of a content image to tokens of a stylized image. Specifically, given a content image  $I$  we first downsample  $I$  to get a half-resolution image  $I'$ . Then,  $I'$  is fed to the tokenization encoder (Sec. 3) which extracts a discrete grid of  $k \times k$  source tokens  $X' = E(I')$ .  $X'$  can now be “translated” into a target (discrete) representation  $\hat{Y}$ , where  $\hat{Y}$  is a grid at the original resolution ( $2k \times 2k$ ) and  $\hat{Y} = f(X')$ , being  $f(\cdot)$  the translation function. Finally,  $\hat{Y}$  is fed into the tokenization decoder obtaining the stylized image  $I^s = G(\hat{Y})$ . In the following subsections, we describe the architecture of  $f(\cdot)$  and the way in which it is trained.

### 4.1. Architecture and self-supervised pre-training

For our translation network  $f(\cdot)$  we use a NAT architecture [15] (Sec. 3) which we train from scratch using a self-supervised learning pretext task consisting in predicting the image at full resolution. Specifically, given the downsam-

pled image  $I'$  and its corresponding grid of tokens  $X' = E(I')$ , we use the indexes in  $X'$  to extract the corresponding embeddings from  $C$  (Sec. 3). For each  $x_{i,j} \in X'$ , let  $e_{x_{i,j}}$  be the corresponding embedding in  $C$  and let  $N' = k^2$ . The so obtained set of embeddings is flattened into a sequence, and, for each element  $e_n$  of the sequence ( $1 \leq n \leq N'$ ), we add an absolute positional embedding [38]  $\mathbf{p}_n$ , where  $\mathbf{p}_n$  has the same dimension as  $e_n$ :  $\mathbf{v}_n = e_n + \mathbf{p}_n$ . The final sequence  $V' = \{\mathbf{v}_1, \dots, \mathbf{v}_n, \dots, \mathbf{v}_{N'}\}$  is input to the encoder of  $f(\cdot)$ . Note that an alternative solution is to directly feed  $f(\cdot)$  with (a flattened version of)  $X'$  and let  $f(\cdot)$  learn its own initial token embedding. However, using the embeddings in  $C$  has the advantage of exploiting the image representation of the pre-trained image tokenizer. Moreover, from the original image  $I$  we extract the ground truth  $X = E(I)$ , which is flattened in a sequence of  $N = 4k^2$  tokens.

Finally, following [15], we build a second sequence of input embeddings  $V$ , with cardinality  $N$ , which is fed to the decoder of  $f(\cdot)$ . As mentioned in Sec. 3, differently from NAT, we do not predict fertility values. Instead, we get the input of the decoder by simply replicating each element  $x_{i,j} \in X'$  according to the positional correspondences between the low-resolution image and high-resolution image (as in Fig. 2). The rationale behind this choice is that  $f(\cdot)$  is trained to predict the full-resolution image, and each encoder input ( $e_{x_{i,j}}$ ) corresponds to a patch in the subsampled image  $I'$  and to 4 patches in the full-resolution image  $I$ . Thus, initializing the decoder with 4 replicas of each source-image patch initial embedding provides a coarse-grained signal for the upsampling task. Similar to before, the embeddings extracted from  $C$  are then flattened and added with a new positional encoding.

Both the encoder and the decoder have self-attention layers and no causal masking is used. However, following [15], in the decoder, we mask out each query position ( $n$ ) only from attending to itself. Using  $V'$  and  $V$ ,  $f(\cdot)$  generates  $N$  parallel posterior distributions over the visual vocabulary ( $\{1, \dots, M\}$ ):  $P = f_\theta(V', V)$ , where  $P$  is a  $N \times M$  matrix,  $P_n \in [0, 1]^M$  and  $P_n[y] = p_\theta(Y_n = y | V', V)$ . Using  $Y = \{y_1, \dots, y_n, \dots, y_N\}$ ,  $f(\cdot)$  is trained to maximize:

$$\mathcal{L}_{pre-train}(\theta) = \sum_{n=1}^N \log P_n[y_n]. \quad (2)$$

This pre-training stage is independent of the target style and it can be shared over different styles. After this stage,  $f(\cdot)$  is able to generate realistic low-level details (which are missing in  $I'$ ). In the next, we describe how a specific style is incorporated in  $f(\cdot)$  using a fine-tuning phase.

## 4.2. Style-specific fine-tuning

Given a style description provided with a textual sentence  $t_s$ , the goal is to fine-tune the pre-trained translator

$f(\cdot)$  (Sec. 4.1) to make it generate image details in the style of  $t_s$ . We fine-tune only the decoder of  $f(\cdot)$ , keeping frozen the encoder. To ensure both stylization and content preservation, we design a prompt that consists of two parts, i.e., a style description  $t_s$  and an image caption  $t_a$ , which describe the image content and can be obtained from a generic image captioning dataset. For instance, given  $t_a = "A man's hand is adjusting his black tie"$  and  $t_s = "cartoon"$ , we obtain  $t_q = "a cartoon of a man's hand is adjusting his black tie"$ . On the other hand, in order to represent the image generated by  $f(\cdot)$ , we first need to sample the distributions in  $P$  (Sec. 4.1), and we do so using multinomial sampling:

$$\hat{Y}_n = Sampling(P_n[y]), \quad \forall n \in \{1, \dots, N\}. \quad (3)$$

The sampled sequence  $\hat{Y}$  is reshaped to a  $2k \times 2k$  grid and fed to the image detokenizer to get the final image  $I^s = G(\hat{Y})$ . Finally, using the CLIP visual and textual encoders we compute the cosine similarity on the CLIP space:

$$r = Sim_{CLIP}(I^s, t_q). \quad (4)$$

However, directly using Eq. 4 as the fine-tuning objective function is not possible because Eq. 3 is not differentiable. In addition, since there is no ground truth for the tokens of stylized images we use RL to encourage the model to explore the answers in the latent space of a pretrained vector-quantized model. We use the REINFORCE algorithm [42] that updates the parameters of  $f_\theta(\cdot)$  using the CLIP-based reward  $r$ , which could keep awarding the model for achieving better-stylized results until the model reaches a limit. This leads to the gradient estimate:

$$\nabla_{\theta|d} \mathcal{L}_{fine-tune}(\theta|d) = \sum_{n=1}^N r \nabla_{\theta|d} \log P_n[y_n], \quad (5)$$

where  $\theta|d$  indicates the parameters of the decoder only (we found fine-tuning both could lead to content loss). By maximizing Eq. 5 we encourage  $f(\cdot)$  to generate images having both the content and the style of the prompt  $t_q$ .

With respect to the whole method, the reason we use down-sampled versions of the content image is that “style” is commonly assumed to be involved in the low-level visual details, such as colors, texture, painting strokes, etc.  $X'$ , which in our formulation represents  $I$  at a lower resolution, presumably keeps most of the content in  $I$  discarding some details, this way facilitating the style translation process. Preliminary experiments (in Appendix A.2) in which we fed the encoder with tokenized full-resolution images led to poor results, demonstrating that the different cardinality between the source and the target sequence is an essential component in this translation process.



Figure 3: Qualitative results of StylerDALLE-1 on various styles: (a) Monet Sunrise, (b) Picasso cubism, (c) Van Gogh blue color, (d) Van Gogh purple color, (e) warm and relaxing, (f) ukiyo-e print, (g) fauvism, (h) pixel art illustration. The style references at the top are for illustration only (not used as input to the model).

## 5. Experiments

### 5.1. Training Details

We implement our method based on two types of pre-trained vector-quantized tokenizer: 1) the officially released dVAE of DALL-E 1 [27] and 2) the VQGAN of Ru-DALLE [39], and consequently obtain two groups of results, noting as StylerDALLE-1 and StylerDALLE-Ru, respectively. We use the two models in our experiment because they are open-sourced while our method is applicable to any large-scale pretrained vector-quantized tokenizer.

To train the model, we use the MS-COCO [23] train-set, which contains 83k images of common objects in daily scenes. In the self-supervised pretraining stage, we only use the images while in the style-specific fine-tuning stage we use both images and captions. The StylerDALLE NAT model consists of a 4-layer encoder and an 8-layer decoder while the attention head number is 8 and the hidden dimension is 512. We use Pytorch [29] to implement our method. We train the NAT model for 25 epochs with a learning rate of 1e-4. We use Adam [18] optimizer. In the style-specific fine-tuning stage, we use both the images and the captions. In particular, we utilize all the caption annotations to en-

hance the model robustness, as usually human-beings annotate different captions of a single image. Notably, the caption annotations are only used at the fine-tuning stage. In other words, StylerDALLE does not need to use image caption as input at inference time. We only fine-tune the decoder of the NAT model, and keep the encoder frozen. We use Adam optimizer with a learning rate of 1e-6. For CLIP model, we use the CLIP ViT-B/32 model. For both training stages, the model is trained on a single RTX-A6000 GPU for 24 hours.

### 5.2. Experimental Results

In the following, we present qualitative, quantitative, and user study results of our method and comparative methods, as well as comparisons with reference image-based methods. The additional implementation details, ablation study, inference time comparison, and additional experimental results are shown in Appendix A.1, A.2, A.3, and A.5, respectively.

**Qualitative Results.** In Fig. 1, Fig. 3 and Fig. 4, we show that our method can effectively transfer various types of styles, i.e., a) abstract art styles, e.g., “fauvism” and

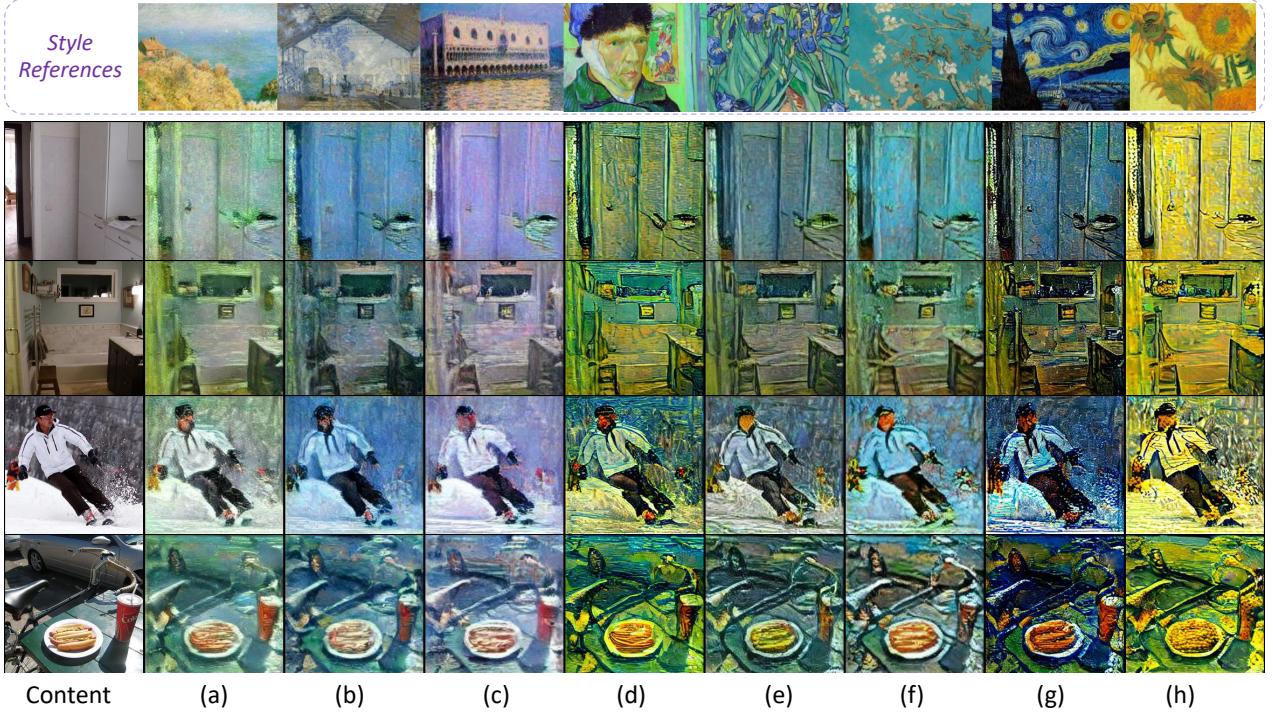


Figure 4: Qualitative results of StylerDALLE-Ru on various styles: (a) Monet, (b) Monet Paris, (c) Monet Venice, (d) Van Gogh, (e) Van Gogh Irises, (f) Van Gogh Almond, (g) Van Gogh Starry Night, (h) Van Gogh Sunflowers. The style references at the top are for illustration only (not used as input to the model).

Dataset	Method	Style	Fauvism	Monet	Monet Sunrise	Monet Sunset	Monet Paris	Van Gogh Irises	Van Gogh Almond Blossoms
CoCo	CLIPStyler-Fast	26.11	27.46	24.78	26.70	27.60	26.23	27.05	
	Ours	<b>30.61</b>	<b>27.72</b>	<b>28.81</b>	<b>30.68</b>	<b>29.63</b>	<b>28.14</b>	<b>31.64</b>	
AFHQ	CLIPStyler-Fast	26.52	26.08	23.27	25.05	25.42	23.28	24.31	
	Ours	<b>29.96</b>	<b>26.55</b>	<b>26.58</b>	<b>29.11</b>	<b>26.10</b>	<b>28.04</b>	<b>31.92</b>	
ImageNet-100	CLIPStyler-Fast	26.63	27.16	24.33	26.12	27.28	26.32	26.23	
	Ours	<b>30.22</b>	<b>27.53</b>	<b>28.29</b>	<b>30.28</b>	<b>27.67</b>	<b>28.26</b>	<b>31.60</b>	

Table 1: Quantitative comparisons with CLIPstyler [20] on different types of styles and datasets.

“pop art”; b) artist-specific styles, e.g., “Monet” and “Van Gogh”; c) artist-specific styles with additional descriptions, e.g., “Monet Paris” and “Van Gogh Sunflowers”; d) artistic painting types, e.g., “pixel art illustration”; and e) emotional effects, e.g., “warm and relaxing”. According to the qualitative results, we draw the following conclusions: 1) StylerDALLE can transfer abstract style concepts which go beyond the texture and color features and are similar to the typical trait of the artist/artistic target style; 2) each style corresponds to generated images that are different from those of other styles; 3) the image content is well preserved;

and 4) StylerDALLE can be applied to open-domain content images (i.e., the image content can contain animals, human beings, daily objects, buildings, etc.).

Further, we compare StylerDALLE with the recent language-guided style transfer method CLIPStyler [20]. CLIPStyler proposes two methods: 1) CLIPStyler-Optimization, which optimizes a style transfer network *for each content image*, thus being time-consuming; and 2) CLIPStyler-Fast, which is the most comparable method to ours as it trains a network *for each style*, and then it can be used with any content images. As shown in Fig. 5,

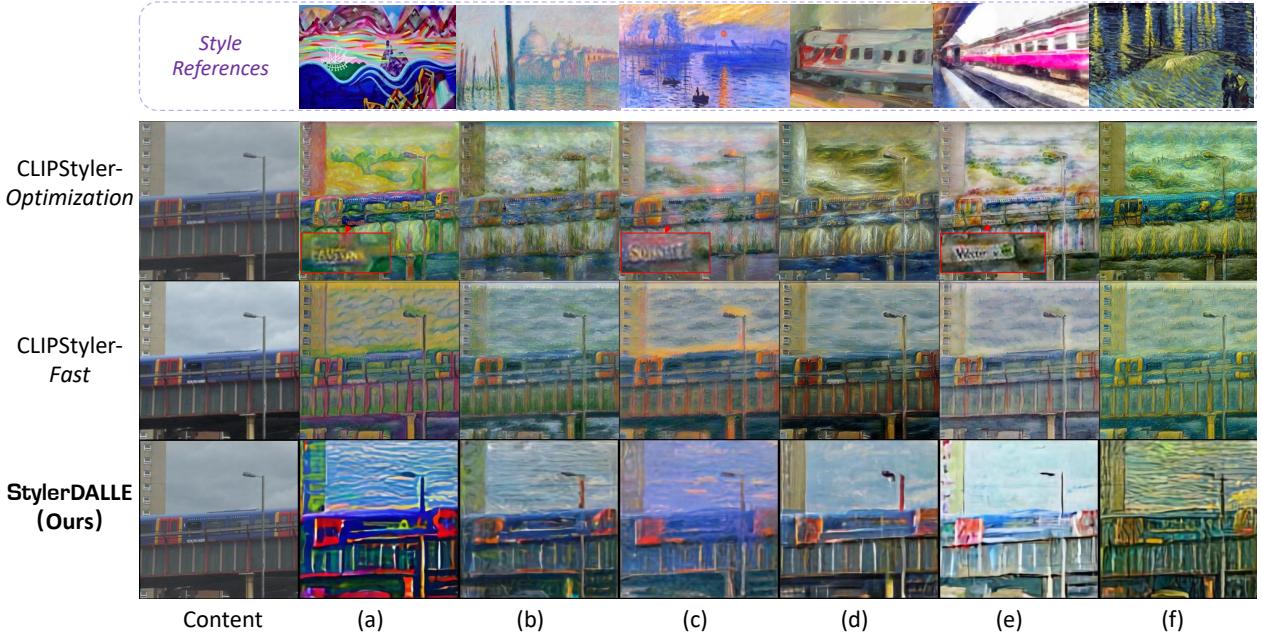


Figure 5: Comparisons with language-guided methods. The styles are (a) fauvism, (b) Monet, (c) Monet Impression Sunrise, (d) oil painting, (e) watercolor painting, (f) Van Gogh, (g) Van Gogh blue color. The style references at the top are for illustration only (not used as input to the model).

CLIPStyler-Optimization generates diverse stylized results but it suffers from inharmonious artifacts. For instance, in the column “Monet”, there are many plants on the train. In addition, CLIPStyler-Optimization has the problems of writing the style text in the results, as in the results of ”fauvism” and so on. On the other hand, the images generated by CLIPStyler-Fast do not contain artifacts but there is less variation among different styles. Importantly, it is hard to recognize the typical trait of each artistic style, and the main differences among the styles are the colors. In contrast, the results of StylerDALLE are much closer to the artworks of the specific artistic style, they show distinct differences among different styles, and they have no artifact issues.

**Quantitative Results.** To do quantitative analysis, we use the CLIP similarity score, formalized as  $score = Sim_{CLIP}(I, t_s)$ , which is computed between generated stylized images and textual description of the target style. In Tab. 1, we present the results of StylerDALLE-1 and CLIPstyler-Fast. Since both methods are applicable for arbitrary content images, we use the MS-COCO val-set, AFHQ val-set [6], and ImageNet-100 val-set [7] for evaluation. According to the results on multiple datasets, although the way we use CLIP is to compute rewards in Reinforcement Learning, instead of directly using CLIP-scores to optimize the network as CLIPstyler, we achieve comparable

(%)	CLIPstyler-Fast	StylerDALLE-1	StylerDALLE-Ru
Preference	15.90	15.33	<b>68.76</b>

Table 2: Preference scores of user study.

and even better quantitative results, indicating the effectiveness of our method.

**User Study.** We conduct a user study to see human opinions towards the stylized images coming from different methods: 1) CLIPstyler-Fast, 2) StylerDALLE-1, and 3) StylerDALLE-Ru. In specific, we collect opinions from 35 human subjects with a 30-question questionnaire. In each question, we ask them to select one stylized result that is closest to a target style. As in Tab. 2, among the three methods, StylerDALLE-Ru achieves the highest preference score of 68.76%, indicating the superiority of our method. We also find that humans prefer StylerDALLE-Ru much more than StylerDALLE-1. We infer this could be because the results from StylerDALLE-1 are blurry, as they are based on the dVAE of DALLE-1, and humans dislike blurry images. More user study details are given in A.4.

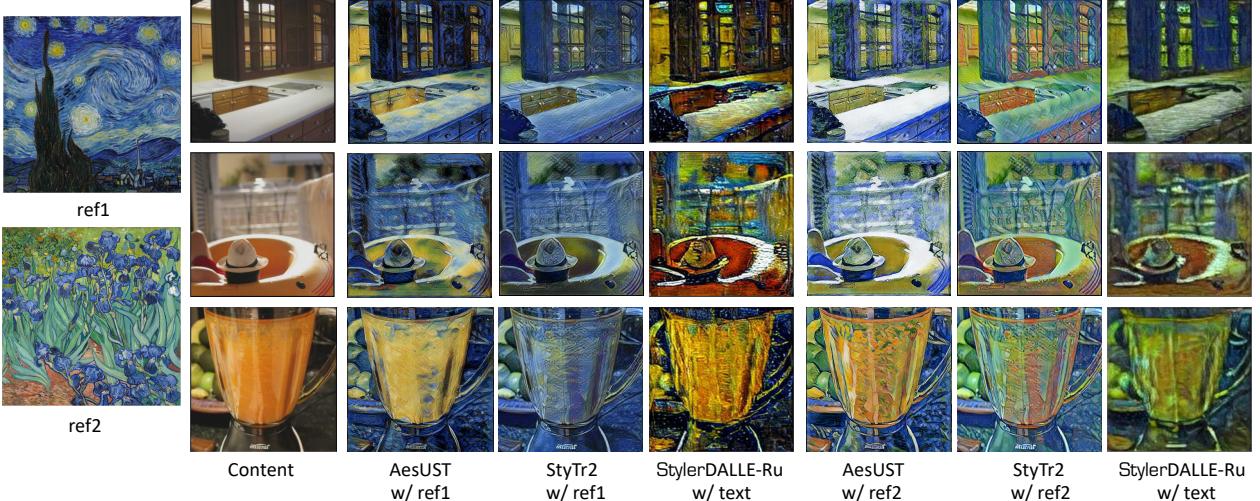


Figure 6: Comparisons with reference image-based methods. StylerDALLE is able to transfer more abstract concepts, e.g., specific painting strokes, and is less likely to produce semantic errors.

#### Comparisons with Reference Image-Based Methods.

We compare StylerDALLE with state-of-the-art reference image-based methods: 1) AesUST [40], an arbitrary style transfer method which enhances the aesthetic reality using a GAN trained with a collection of artworks; and 2) StyTr2 [9], an arbitrary style transfer method which uses a transformer to eliminate the biased content representation issues of CNN-based methods. To make the comparison feasible, we show the results of AesUST and StyleTr2 using two Van Gogh paintings as the reference images, and the results of StylerDALLE trained using the corresponding language description.

As shown in Fig. 6, the results of StylerDALLE are distinctive from the results of reference image-based methods. In concrete, the results of both AesUST and StyleTr2 are mostly affected by the colors and the textures of the reference images, and to some extent in an unnatural way. For instance, on the bottom line, in the “Van Gogh Irises” stylized results of AesUST and StyleTr2, the textures of the irises get transferred to the orange cup. In transferring the style of “Van Gogh Starry Night”, the objects in the results of AesUST and StyleTr2 are mostly in the same dark-sky blue as the reference image, making the scenes a bit in-realistic. By contrast, the colors and textures used in the reference style are well transferred while being appropriately applied to the contents, without changing the original semantics. Moreover, StylerDALLE achieves to transfer higher-level style features, e.g., the brushstroke, rather than merely colors and textures, leading to the results of a similar style to the target one. For example, the strokes in *Starry Night* are sharper as compared to the ones in *Irises*, and the differences are also

presented in the stylized results of StylerDALLE.

## 6. Conclusion

We present StylerDALLE, a language-guided style transfer method that leverages the power of the large-scale pretrained vector-quantized image tokenizer and CLIP. Specifically, inspired by natural language translation, we propose a non-autoregressive sequence translation approach to manipulate the discrete visual tokens, from the content image to the stylized image. We use Reinforcement Learning to include CLIP-based language supervision on the style and content. Differently from previous work, StylerDALLE can transfer abstract style concepts that are implicitly represented in the pretrained image tokenizer and CLIP and which cannot be easily obtained using reference images. Moreover, using the large-scale pretrained latent space as the basic image representation makes it possible to reduce the artifacts and the semantic incoherence better than the previous work that operates at the pixel level.

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