

# Image Style Transfer CLIPstyler

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## CLIPstyler: Image Style Transfer with a Single Text Condition

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Figure 1. Our style transfer results on various text conditions. Translated images have spatial structure of the content images with realistic textures corresponding to the text.

### Abstract

Existing neural style transfer methods require reference style images to transfer texture information of style images to content images. However, in many practical situations, users may not have reference style images but still be interested in transferring styles by just imagining them. In order to deal with such applications, we propose a new framework that enables a style transfer ‘without’ a style image, but only with a text description of the desired style. Using

only with a single text condition. Specifically, we propose a patch-wise text-image matching loss with multiview augmentations for realistic texture transfer. Extensive experimental results confirmed the successful image style transfer with realistic textures that reflect semantic query texts.

### 1. Introduction

Style transfer aims to transform a content image by transferring the semantic texture of a style image. The seminar

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### Background & Goal

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#### ▶ Previous research limitation

- Existing neural style transfer methods require reference style images
- Tried manipulating images with text conditions, but the performance of the embedding model is limited and the manipulation is restricted to specific content domains

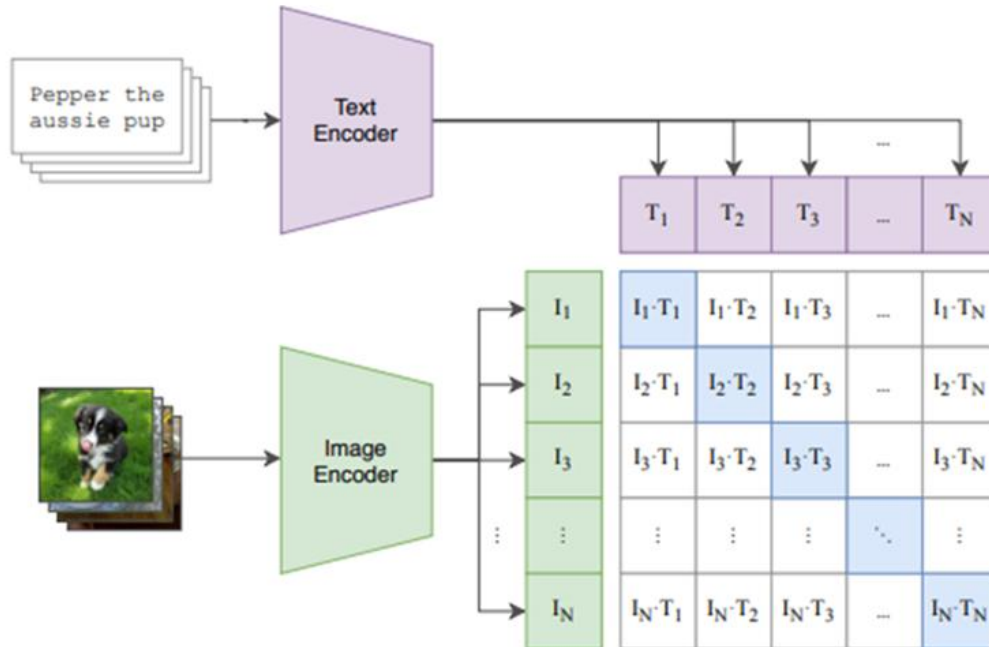
#### ▶ Goal

- Propose a image style transfer method to deliver the semantic textures of text conditions using CLIP

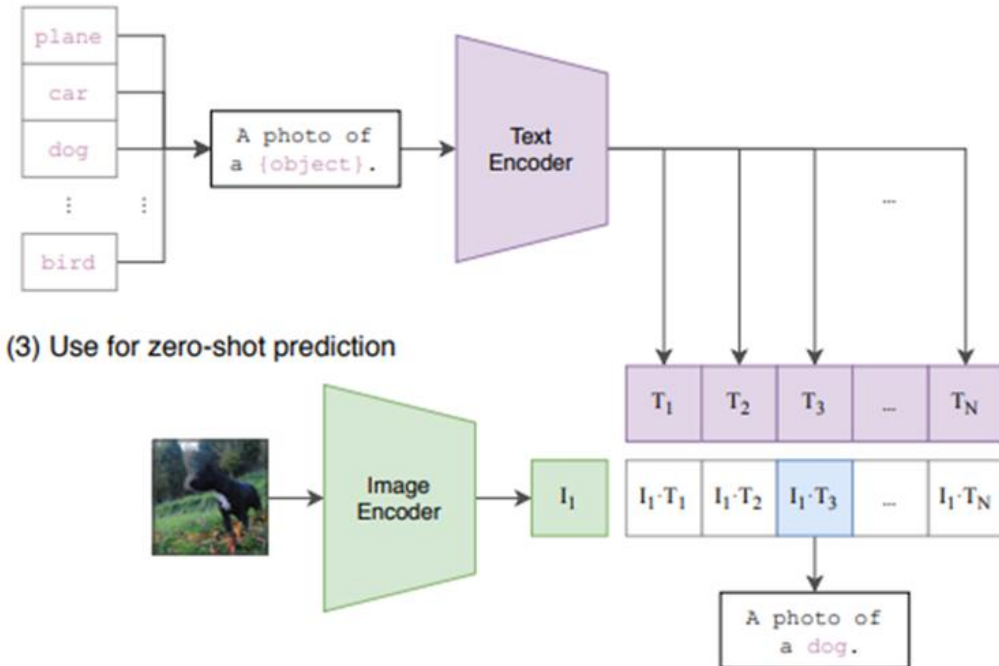
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## CLIP

(1) Contrastive pre-training



(2) Create dataset classifier from label text



(3) Use for zero-shot prediction

Fig 1. Overview of CLIP

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### Network Architecture

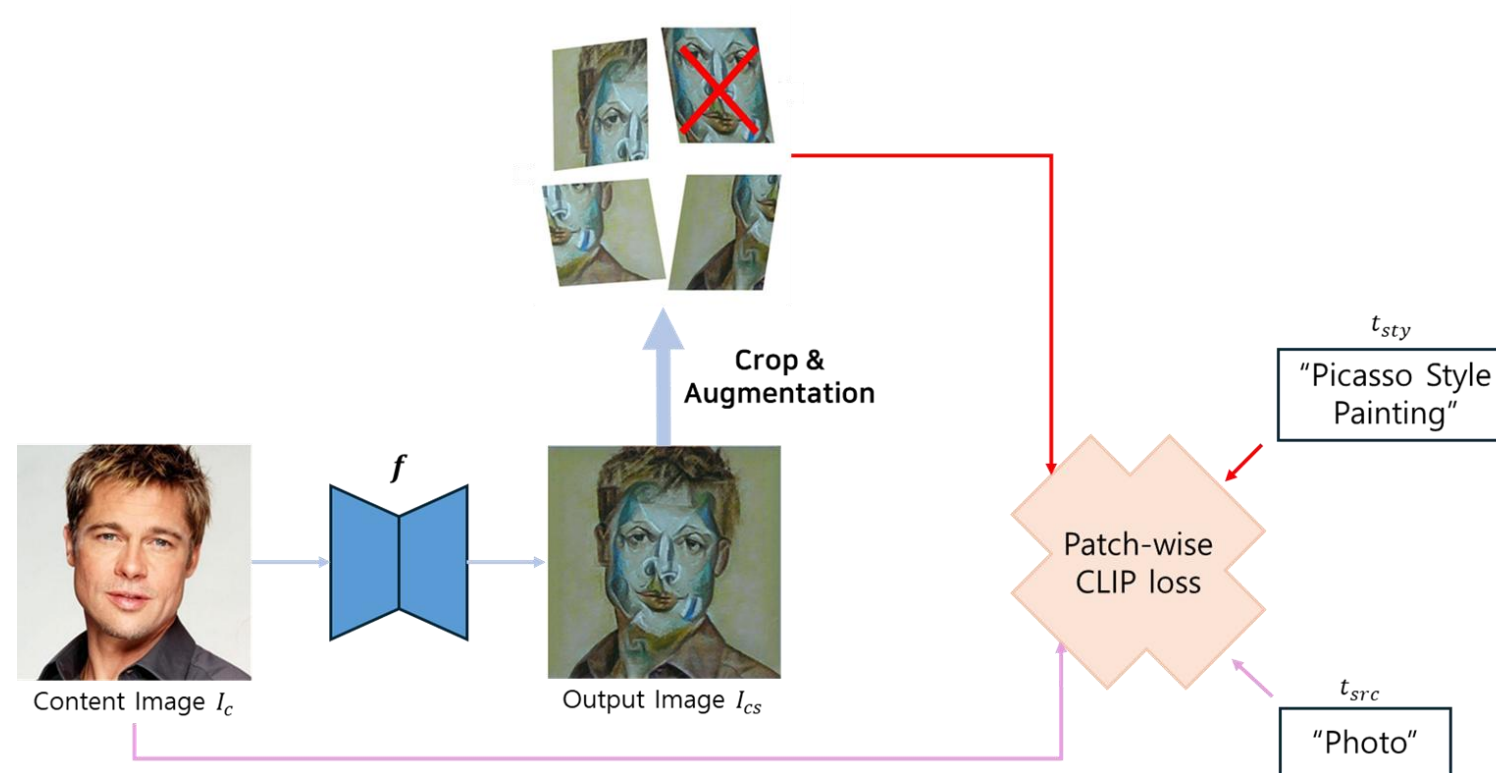


Fig 2. Overview of CLIPStyler

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## Loss functions

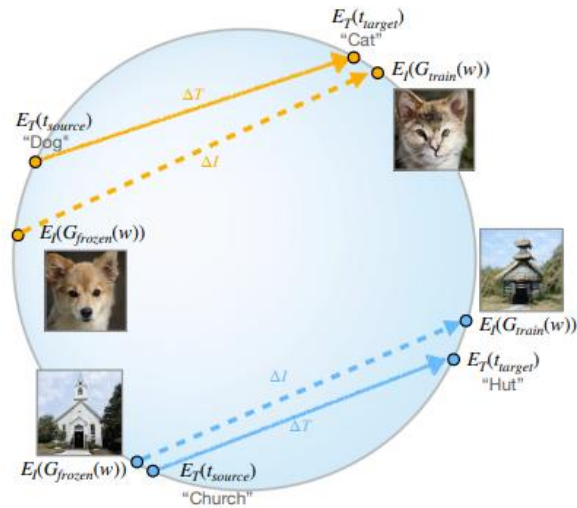
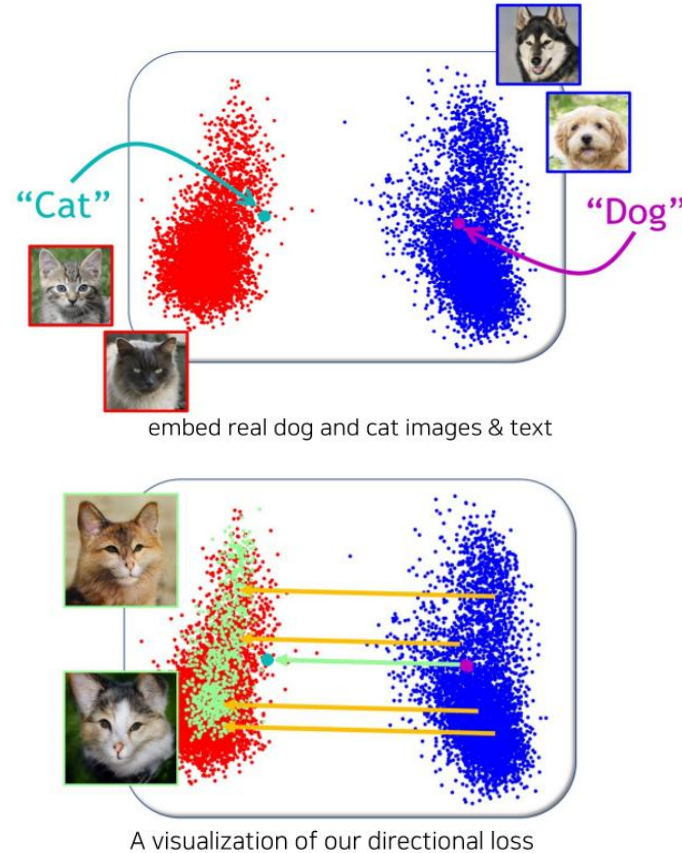


Fig 3. Overview of Directional CLIP loss



### Global CLIP loss

- Employ the directional CLIP loss that aligns the CLIP-space direction between the source and output

$$\Delta T = E_T(t_{sty}) - E_T(t_{src}),$$

$$\Delta I = E_I(f(I_c)) - E_I(I_c),$$

$$L_{dir} = 1 - \frac{\Delta I \cdot \Delta T}{|\Delta I| |\Delta T|},$$

Eq 1. Directional CLIP loss

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## Loss functions

### ► PatchCLIP loss

- CLIPStyler's goal is to apply the semantic texture of  $f_{sty}$  → Global CLIP loss doesn't perfectly match to CLIPStyler
- Propose a PatchCLIP loss that is a method of calculating loss by using patches of an image

### ► Augmentation

- Using Augmentations on each patch assist the network to represent more vivid and diverse textures
- Using Perspective Augmentation, all patches are guided to have the same semantic when viewed in multiple points

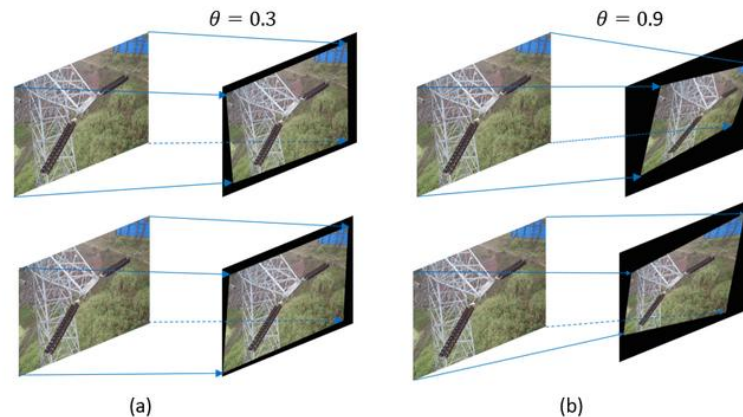


Fig 4. Example of Perspective Augmentation



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### Loss functions

#### ► Threshold Rejection

- Due to stochastic randomness of path sampling and augmentations, method suffer from over-stylization
- Include regularization to reject the gradient optimization process for high-scored patches

#### ► Additional loss

- Content loss: To maintain the content information of input image → calculating the MSE between features of content and output images
- Total Variation loss: To alleviate the side artifacts from irregular pixels

$$\Delta T = E_T(t_{sty}) - E_T(t_{src}),$$

$$\Delta I = E_I(aug(\hat{I}_{cs}^i)) - E_I(I_c)$$

$$l_{patch}^i = 1 - \frac{\Delta I \cdot \Delta T}{|\Delta I| |\Delta T|}, \quad \text{where } R(s, \tau) = \begin{cases} 0, & \text{if } s \leq \tau \\ s, & \text{otherwise} \end{cases}$$

Eq 2. Patch-wise CLIP loss with Threshold rejection

$$L_{patch} = \frac{1}{N} \sum_i R(l_{patch}^i, \tau)$$

$$\mathcal{L}_{\text{content}} = \frac{1}{N} \sum_{i=1}^N (F_l(I_{cs})_i - F_l(I_c)_i)^2$$

Eq 3. Content Loss

$$\mathcal{L}_{TV} = \sum_{i,j} ((I(i+1, j) - I(i, j))^2 + (I(i, j+1) - I(i, j))^2)$$

Eq 4. Total Variation Loss

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## Experiments

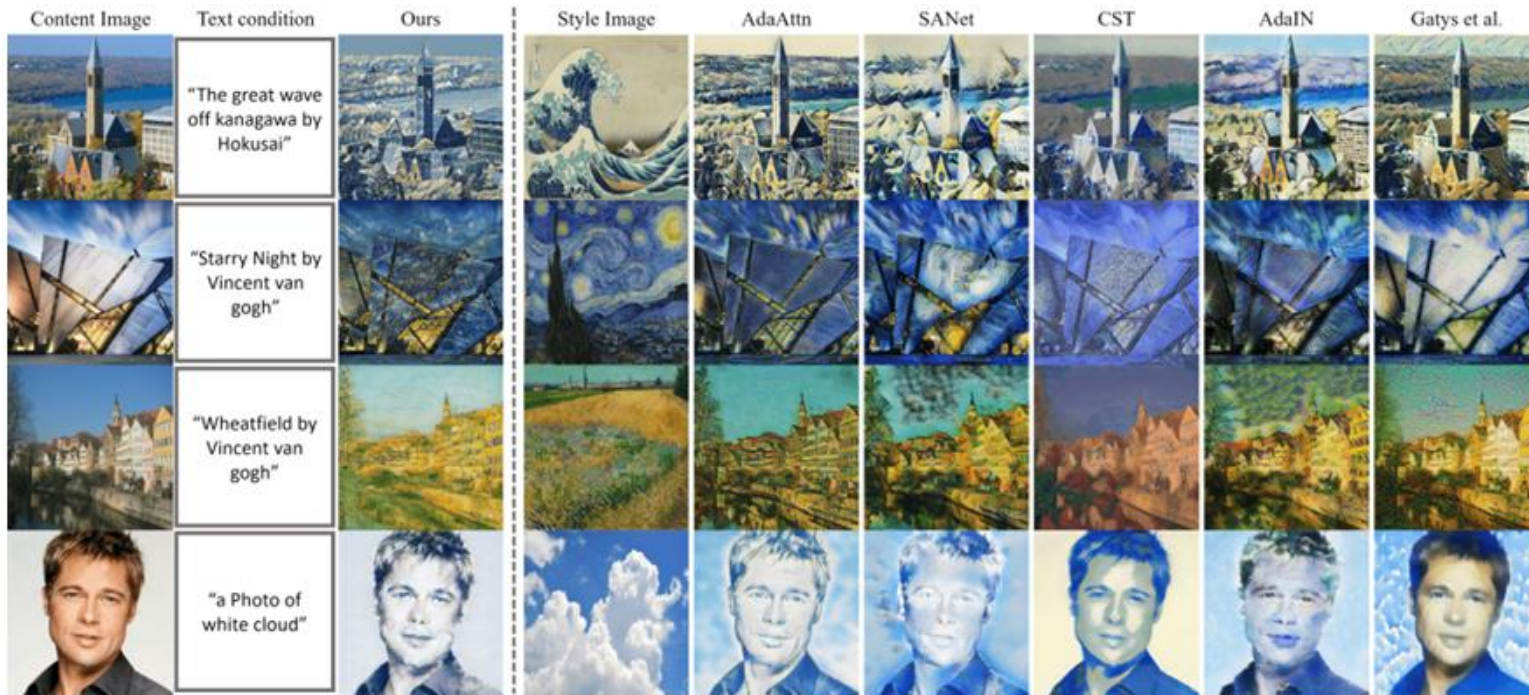


Fig 5. Comparison results with baseline style transfer models



Fig 6. Comparison results with other text-guide d manipulation models



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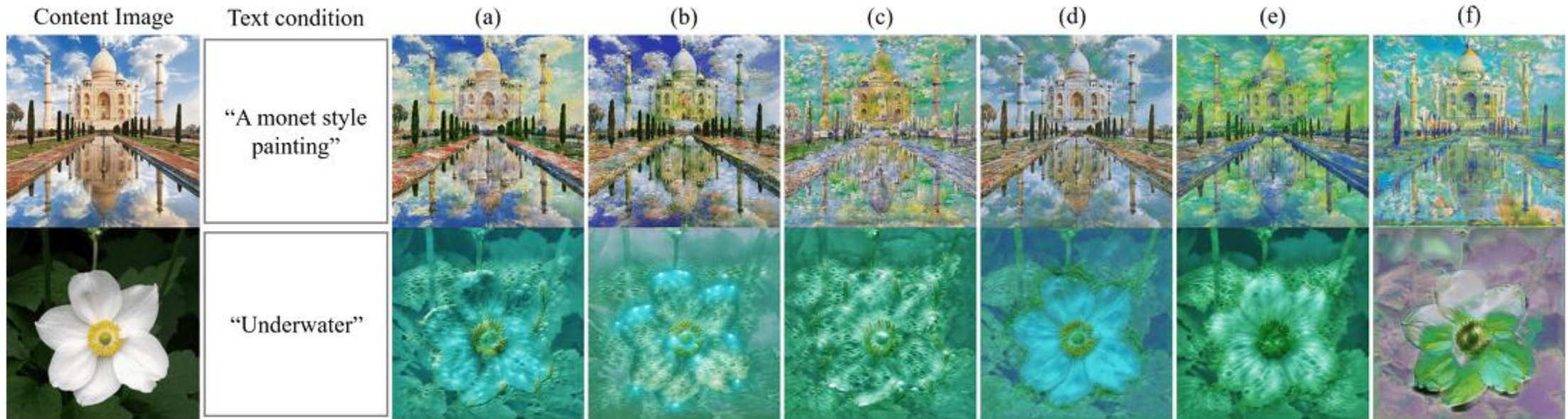


Fig 7. Ablation study results

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### Implications & Limitations

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#### ► Implications

- Proposed a novel image style transfer framework to transfer the semantic texture information only using text condition

#### ► Limitations

- It is difficult to maintain consistency because the generated style may be different even when the same text prompt is entered