

Computer Vision Project

Photorealistic Style Transfer



Project Information



Github Repository: [Link](#)



Reference Paper: Deep Photo
Style Transfer ([link here](#))



Team Members:

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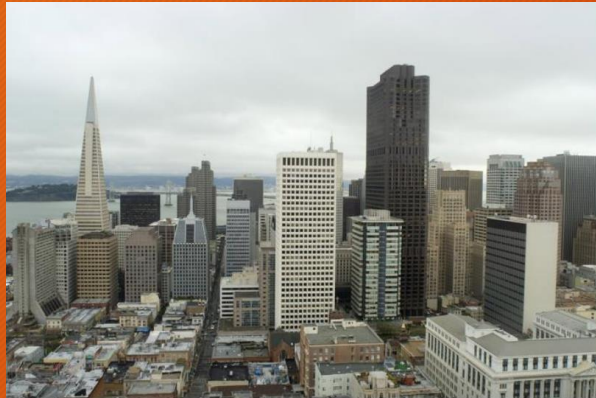
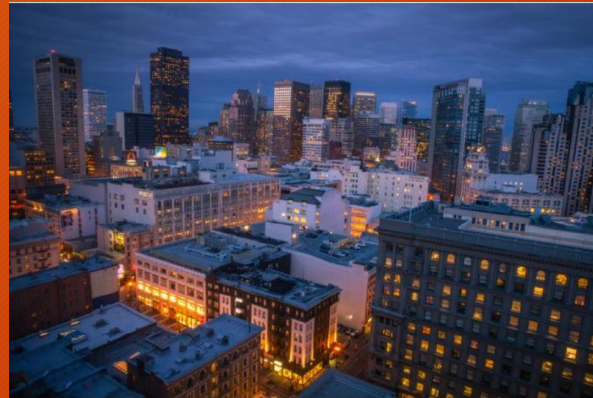
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Problem Statement

Style Image



Content Image

Photo Style Transfer



Transformed Image

Introduction



We want to change the illumination, weather, hue etc. of the input photo.



We want to prevent painting-like distortions and ensuring that the photorealistic properties of the input images.



Maintain the semantics of the image and not match incompatible parts of the reference and the input image.

A 3D rendering of a red puzzle piece standing out from a field of white puzzle pieces. The red piece is in the center, slightly raised, and has a glossy finish. The white pieces are arranged in a grid-like pattern around it, with some pieces missing, creating a sense of a puzzle being solved or a missing link.

Proposed Model Features

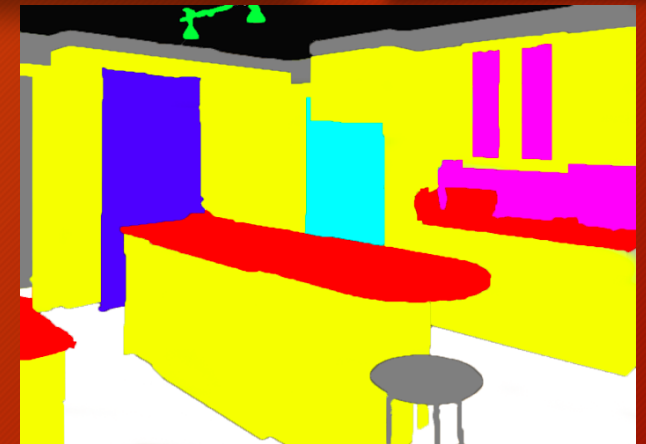
Segmentation

The process of partitioning a digital image into multiple segments i.e. sets of pixels, also known as image objects.

Used to locate objects and boundaries like lines, curves, etc. in images.

We create the segmentations of both content and style images

We use the segmented images in the dataset.



VGG-19 Base Model

- We use this to get the base weights from content and style image.
- It is a pre-trained model.
- VGG-19 is a Convolutional Neural Network which has 19 layers.
- It has been trained using more than 1 million images from the ImageNet Database

Matting Laplacian

- A natural Image Matting method
- Extracting FG from BG so that the colour of one object does not go into another.
- We perform matting on the content image and return Matrix
- Matrix is used for affine loss

$$\sum_k |(i,j) \in w_k| \left(\delta_{ij} - \frac{1}{|w_k|} \left(1 + (I_i - \mu_k) \left(\sum_k + \frac{\epsilon}{|w_k|} I_3 \right)^{-1} (I_j - \mu_k) \right) \right)$$

Comparison with Matting

Without Matting



With Matting



Affine Loss

- Make the image smoother
- More Photo realistic images
- Uses the Matrix returned from Matting Laplacian
- Conserves the locally affine nature of the image.
- Leads to sharper images to prevent distortions.

$$\mathcal{L}_m = \sum_{c=1}^3 (V_c[O]^T M_I V_c[O])$$

Comparison after Smoothing



Base Neural Style Algorithm

Base Content Loss

$$\mathcal{L}_s^l = \frac{1}{2N_l^2} \sum_{ij} (G_l[O] - G_l[S])_{ij}^2$$

Base Style Loss

$$\mathcal{L}_c^l = \frac{1}{2N_l D_l} \sum_{ij} (F_l[O] - F_l[I])_{ij}^2$$

Augmented Functions

Photorealism Loss

$$\mathcal{L}_m = \sum_{c=1}^3 (V_c [O]^T M_I V_c [O])$$

Augmented Style Loss

$$\mathcal{L}_{s+}^l = \sum_{c=1}^C \frac{1}{2N_{l,c}^2} \sum_{ij} (G_{l,c}[O] - G_{l,c}[S])_{ij}^2$$

Augmented Objective

$$\mathcal{L}_{total} = \sum_{l=1}^L \alpha_l \mathcal{L}_c^l + \Gamma \sum_{l=1}^L \beta_l \mathcal{L}_{s+}^l + \lambda \mathcal{L}_m$$

Without augmented style loss

Style Image



Content Image

Photo Style Transfer



Transformed Image

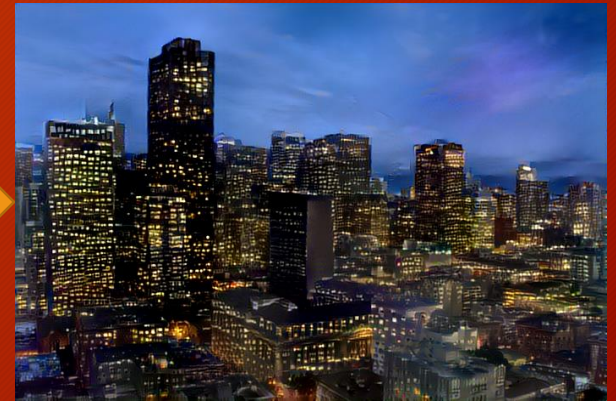
With augmented style loss

Style Image



Content Image

Photo Style Transfer



Transformed Image

Outputs:

Content Image



Style Image



Final Image



Content Image



Style Image



Final Output



Content-Image



Style Image



Final Image



Content-Image



Style Image

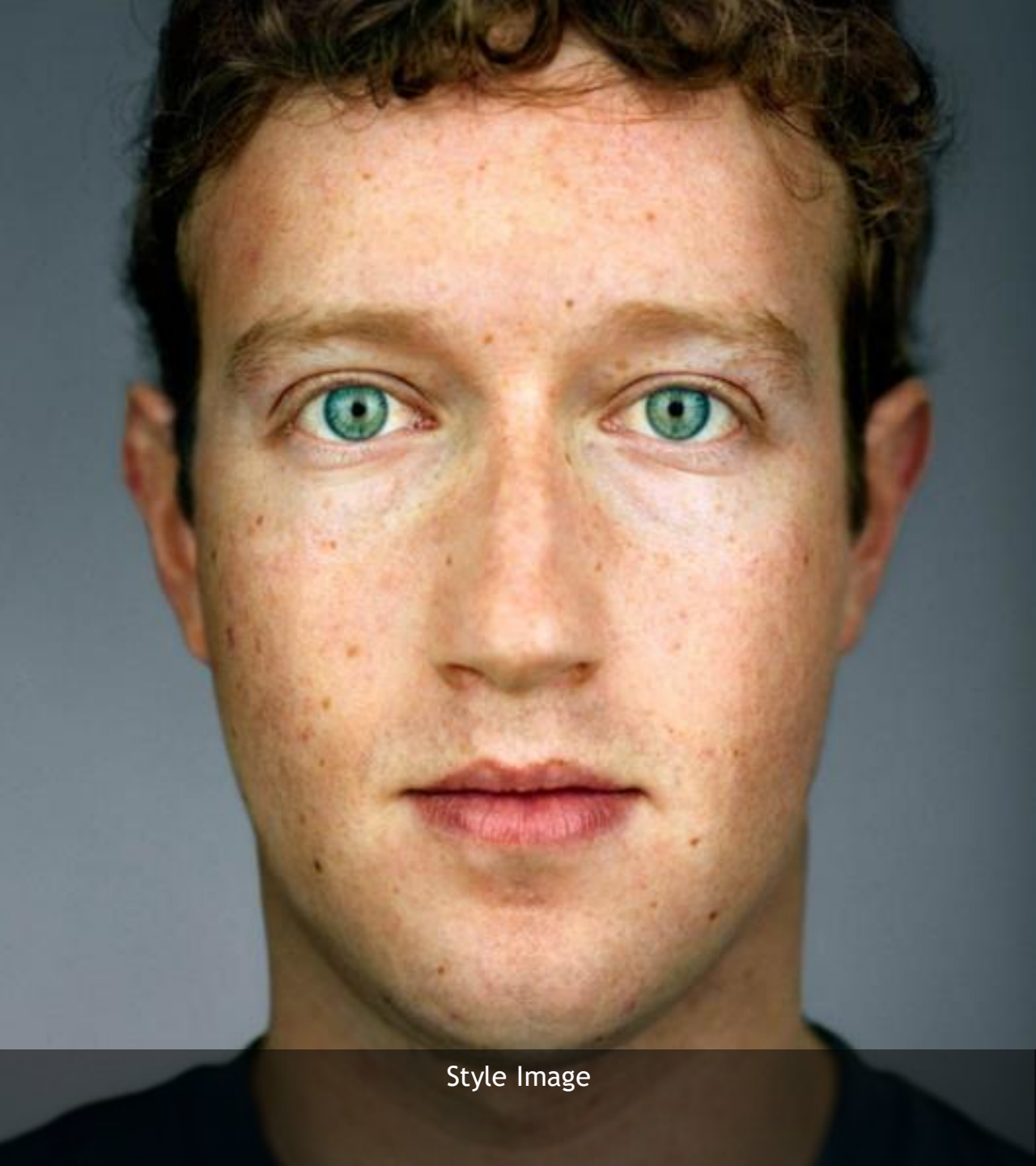


Final Image



Progress over iterations





Style Image



Content Image

Varying Parameters - Content Weight



Content Weight = 3



Content Weight = 4



Content Weight = 5

Varying Parameters - Style Weight



Style Weight = 100



Style Weight = 1000



Style Weight = 10000

Varying Parameters - Photorealism Weight



Photorealism Weight = 1000



Photorealism Weight = 10000



Photorealism Weight = 100000